## Improved time and space complexity for Kianfar's inequality rotation algorithm

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#### Abstract

In this paper, constraint rotation techniques are considered for preconditioning $0-1$ knapsack problems. These techniques permit one to generate new inequalities by means of rotation of the original ones in order to approach the convex hull associated with the feasible integer points. The time and space complexities of Kianfar's inequality rotation algorithm for combinatorial problems are improved. A revisited algorithm with $\mathcal{O}(n \bar{C})$ and $\mathcal{O}(\bar{C})$, representing, time and space complexity, respectively, is proposed, where $\bar{C}$ is smaller than the knapsack capacity. [Submitted 12 April 2008; Accepted 26 May 2008]


Keywords: knapsack problems; constraint rotation techniques; lifting; dynamic programming.

Reference to this paper should be made as follows: El Baz, D., Elkihel, M., Gely, L. and Plateau, G. (2009) 'Improved time and space complexity for Kianfar's inequality rotation algorithm', European J. Industrial Engineering, Vol. 3, No. 1, pp.90-98.

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## 1 Introduction

We concentrate on combinatorial problems of the following form:

$$
\begin{equation*}
\max \left\{\sum_{j=1}^{n} p_{j} x_{j} \mid \sum_{j=1}^{n} w_{i j} x_{j} \leq C_{i}, i=1, \ldots m ; x_{j} \in\{0,1\}, j=1, \ldots ., n\right\} \tag{1}
\end{equation*}
$$

where $C_{i}$ denotes the capacity of the $i$-th knapsack; $m$ and $n$ the number of knapsacks and items, respectively; $p_{j}$ the profit associated with the $j$-th item; and $w_{i j}$, the weight of the $j$-th item in the $i$-th knapsack (see Kellerer et al., 2004; Martello and Toth, 1990; Wolsey, 1998). Without loss of generality, we assume that all data are positive integers. In order to avoid trivial solutions, we assume that we have: $\sum_{j=1}^{n} w_{i j}>C_{i}, i=1, \ldots, m$, and $w_{i j} \leq C_{i}$ for all $i \in\{1 \ldots m\} j \in\{1, \ldots, n\}$.

Many real-world applications can be formulated as problem (1) (see Gavish and Pirkul, 1982; Thesen, 1973; Yang, 2001; Kacem, to appear). Problem (1) is well known to be NP complete. Some multi-knapsack problems may be very difficult to solve. In some cases, a new formulation of a problem that is intractable in reasonable time permits one to solve it more easily. Among the techniques that can be used to reformulate problems, we can quote coefficient reduction (see Bradley et al., 1975), facets (see Wolsey, 1976) and rotation techniques (see Kianfar, 1971).

Constraint rotation techniques allow one to get tighter equivalent formulations of integer linear programming problems (see Kianfar, 1971; 1976). These techniques permit one to generate new inequalities by means of rotation of the original ones in order to
approach the convex hull associated with the feasible integer points. These methods are generally used as a preconditioning. The basic principle of constraint rotation techniques can be presented as in the following equations. For simplicity of presentation, constraints will be denoted in the following form in the sequel:

$$
\begin{equation*}
w x=\sum_{j=1}^{n} w_{j} x_{j} \leq C, \tag{2}
\end{equation*}
$$

with $C, w_{j} \in N^{*}, j \in\{1, \ldots, n\}, \max _{j}\left\{w_{j}\right\} \leq C<\sum_{j=1}^{n} w_{j}$ and $x \in S$ where

$$
\begin{equation*}
S=\left\{x \in\{0,1\}^{n} \mid w x \leq C\right\} . \tag{3}
\end{equation*}
$$

We now introduce the following convex polyhedra related to $S$ :

$$
\begin{equation*}
\bar{S}=\left\{x \in[0,1]^{n} \mid \sum_{j=1}^{n} w_{j} x_{j} \leq C\right\} \tag{4}
\end{equation*}
$$

The rotation of Inequality (2) consists in moving the hyperplane:

$$
\begin{equation*}
w x=\sum_{j=1}^{n} w_{j} x_{j}=C, \tag{5}
\end{equation*}
$$

in such a way that the new hyperplane:

$$
\begin{equation*}
\hat{w} x=\sum_{j=1}^{n} \hat{w}_{j} x_{j}=C \tag{6}
\end{equation*}
$$

passes through more integer points in the space $\bar{S}$ than the original one, so that we obtain a stronger inequality if it is possible. More precisely, the problem consists in obtaining the largest integer $\hat{w}_{i}$ if it exists such that $\hat{w}_{i}>w_{i}$ and $S_{i}=S$, where:

$$
\begin{equation*}
S_{i}=\left\{x \in\{0,1\}^{n} \mid \sum_{j=1, j \neq i}^{n} w_{j} x_{j}+\hat{w}_{i} x_{i} \leq C\right\} \tag{7}
\end{equation*}
$$

This process is repeated for all $i \in\{1, \ldots, n\}$. Finally, we have:

$$
\begin{equation*}
S=\hat{S}=\left\{x \in\{0,1\}^{n} \mid \sum_{j=1}^{n} \hat{w}_{j} x_{j} \leq C\right\} . \tag{8}
\end{equation*}
$$

Let us now define the following sets:

$$
\begin{align*}
& \overline{\hat{S}}=\left\{x \in[0,1]^{n} \mid \sum_{j=1}^{n} \hat{w}_{j} x_{j} \leq C\right\},  \tag{9}\\
& H=\left\{x \in\{0,1\}^{n} \mid w x=C\right\}  \tag{10}\\
& \hat{H}=\left\{x \in\{0,1\}^{n} \mid \hat{w} x=C\right\} \tag{11}
\end{align*}
$$

The sets $H$ and $\hat{H}$, denote the intersections of the set $S$ with the hyperplanes $w x=C$ and $\hat{w} x=C$, respectively. Then, we have (see Kianfar, 1971; 1976):

$$
\begin{equation*}
\overline{\hat{S}} \subset \bar{S} \text { and } H \subset \hat{H} \tag{12}
\end{equation*}
$$

Thus, the first relation implies that constraint rotation will permit one to obtain a stronger inequality, i.e., the domain may be smaller, though it contains the same integer points. The second relation traduces the fact that the new constraint passes through as many integer points as possible.

In Section 2, we recall first the principles of the constraint rotation algorithm proposed by Kianfar (see Kianfar, 1971; 1976). Then, we propose a revisited algorithm which improves the time and space complexities. Section 3 provides a brief conclusion.

## 2 Efficient inequality rotation algorithm

In this section, we present an efficient algorithm which performs constraint rotation with improved time and space complexities, as compared with Kianfar's method (see Kianfar, 1971; 1976, see also Elkihel, 1984).

### 2.1 Constraint rotation technique

We first present the principles of the constraint rotation algorithm proposed by Kianfar. The technique used consists in performing coefficient modifications of Constraint (2) recursively as follows, starting from the $n$-th component, denoted by $x_{n}$, to the first one, denoted by $x_{1}$. We concentrate first on component $x_{n}$ and consider the problem:

$$
\begin{equation*}
v(n)=\max \left\{\sum_{j=1}^{n-1} w_{j} x_{j} \mid \sum_{j=1}^{n-1} w_{j} x_{j} \leq C-w_{n}, x_{j} \in\{0,1\}, j \in\{1, \ldots, n-1\}\right\} \tag{13}
\end{equation*}
$$

If $v(n)<C-w_{n}$, then constraint rotation is performed and $w_{n}$ takes the new value $\hat{w}_{n}$ such that:

$$
\begin{equation*}
\hat{w}_{n}=w_{n}+\left(C-w_{n}-v(n)\right)=C-v(n), \tag{14}
\end{equation*}
$$

so that the new hyperplane contains at least one integer point with $x_{n}=1$. Otherwise, the value of $w_{n}$ remains unchanged. For $k=n-1, n-2, \ldots, 2$, consider now this series of problems:

$$
v(k)=\max \left\{\begin{array}{l}
\sum_{j=1}^{k-1} w_{j} x_{j}+\sum_{j=k+1}^{n} \hat{w}_{j} x_{j} \mid \sum_{j=1}^{k-1} w_{j} x_{j}+\sum_{j=k+1}^{n} \hat{w}_{j} x_{j} \leq C-w_{k},  \tag{15}\\
x_{j} \in\{0,1\}, j \in\{1, \ldots, k-1\} \cup\{k+1, \ldots, n\}
\end{array}\right\} .
$$

If $v(k)<C-w_{k}$, then one performs rotation of constraint and $w_{k}$ takes the value $\hat{w}_{k}$, given as follows:

$$
\begin{equation*}
\hat{w}_{k}=w_{k}+\left(C-w_{k}-v(k)\right)=C-v(k), \tag{16}
\end{equation*}
$$

in such a way that the new hyperplane contains at least one integer point with $x_{k}=1$. Otherwise, one does not change the value of $w_{k}$ This process is repeated till $k=2$. For $k=1$ :

$$
\begin{equation*}
v(1)=\max \left\{\sum_{j=2}^{n} \hat{w}_{j} x_{j} \mid \sum_{j=2}^{n} \hat{w}_{j} x_{j} \leq C-w_{1}, x_{j} \in\{0,1\}, j \in\{2, \ldots, n\}\right\} . \tag{17}
\end{equation*}
$$

If $v(1)<C-w_{1}$, then constraint rotation is performed and $w_{1}$ takes the new value $\hat{w}_{1}$. such that:

$$
\begin{equation*}
\hat{w}_{1}=w_{1}+\left(C-w_{1}-v(1)\right)=C-v(1), \tag{18}
\end{equation*}
$$

so that the hyperplane will contain at least one integer point with $x_{1}=1$. Otherwise, in a way similar to the situations quoted above, the value of $w_{1}$ remains unchanged.

We recall that the Kianfar algorithm, which is based on the above technique, has $\mathcal{O}\left(n^{2} C\right)$ time complexity and $\mathcal{O}(n C)$ space complexity (see Kianfar, 1971; 1976).

In the next subsection, we propose a revisited constraint rotation algorithm based on dynamic programming with improved time and space complexities.

### 2.2 Revisited constraint rotation algorithm

The algorithm relies on the technique presented in the previous subsection. Components will be computed using the dynamic programming list method. The algorithm is decomposed into two steps. In the first step, Problem (13) is solved using the dynamic programming list method (see Ahrens and Finke, 1975; Plateau and Elkihel, 1985). The list generated by the first step is used in order to prepare computations performed during the second step, where series of Problems (15), $k=n-1, n-2, \ldots, 2$ and (17), for $k=1$, are solved using the dynamic programming list method.

Step 1
The dynamic programming list method proposed by Ahrens and Finke (see Ahrens and Finke, 1975) is based on the concepts of list and dominance. In Step 1, we shall recursively generate lists $L_{k}$ of pairs $(w, p), k=1,2, \ldots, n-1$, where $w$ is a weight and $p \leq k$ is the dynamic programming stage number at which pair ( $w, p$ ) was created. Initially, we have $L_{0}=\{(0,0)\}$.

Let us define first the set $N_{k}$ of new pairs generated at stage $k$, where new pairs result from the fact that a new item, i.e., the $k$-th item, was taken into account. We have:

$$
\begin{equation*}
N_{k}=\left\{\left(w+w_{k}, k\right) \mid(w, p) \in L_{k-1}, w+w_{k} \leq \bar{C}\right\}, \tag{19}
\end{equation*}
$$

where

$$
\begin{equation*}
\bar{C}=C-\min _{j \in\{1, \ldots, n\}} w_{j} \tag{20}
\end{equation*}
$$

Note that $\bar{C}$ is introduced here in order to diminish the total work. According to the dominance principle, which is a consequence of Bellman's optimality principle, all pairs $(w, p) \in L_{k-1} \cup N_{k}$ obtained by construction such that there exists a pair
$\left(w^{\prime}, p^{\prime}\right) \in L_{k-1} \cup N_{k}$, which satisfies: $w=w^{\prime}$ and $p^{\prime}<p$, must not belong to a list $L_{k}$. In this case, we usually say that the pair ( $w^{\prime}, p^{\prime}$ ) dominates the pair ( $w, p$ ). Thus, we can define as follows the set $D_{k}$ of dominated pairs at stage $k$ :

$$
\begin{gather*}
D_{k}=\left\{(w, p) \mid(w, p) \in L_{k-1} \cup N_{k}, \exists\left(w^{\prime}, p^{\prime}\right) \in L_{k-1} \cup N_{k}\right. \text { with }  \tag{21}\\
\left.w=w^{\prime}, p^{\prime}<p\right\}
\end{gather*}
$$

For all positive integers $k$, the dynamic programming recursive list $L_{k}$ is defined as follows:

$$
\begin{equation*}
L_{k}=L_{k-1} \cup N_{k}-D_{k} . \tag{22}
\end{equation*}
$$

Note that the lists $L_{k}$ are organised as sets of monotonically increasing ordered pairs by weight. From the list $L_{n-1}$ we can derive the value of $w_{n}$ according to Equation (14) with:

$$
\begin{equation*}
v(n)=\max \left\{w \mid w \leq C-w_{n},(w, p) \in L_{n-1}\right\} . \tag{23}
\end{equation*}
$$

Remark 1. Note that only one list is stored in the memory, i.e., the currently growing list $L_{k}$. Thus, at the end of Step 1, all data necessary to perform Step 2 will be contained in the list $L_{n-1}$. Note also that the lists $L_{k}$ of pairs ( $w, p$ ) can be derived easily from $L_{n-1}$ as follows, using the index $p$ :

$$
\begin{equation*}
L_{k}=\left\{(w, p) \in L_{n-1} \mid p \leq k\right\} . \tag{24}
\end{equation*}
$$

As a consequence, the space complexity of Step 1 is $\mathcal{O}(\bar{C})$. Note that the time complexity of computing $v(n)$ is $\mathcal{O}(\bar{C})$. Note also that each list $L_{k}$ is generated with time complexity $\mathcal{O}(\bar{C})$. Thus, the time complexity of Step 1 is $\mathcal{O}(n \bar{C})$.

## Step 2

In a way quite similar to Step 1 , we can recursively generate lists $\hat{L}_{k}$ of weights $w$, starting from $k=n$ to $k=2$. Let us consider first the set $\hat{L}_{n+1}$ such that:

$$
\begin{equation*}
\hat{L}_{n+1}=\{0\} . \tag{25}
\end{equation*}
$$

We define as follows the set $\hat{N}_{k}$ of new weights generated at stage $k$, where new weights result from the fact that a new item, i.e., the $k$-th item, is taken into account at this stage:

$$
\begin{equation*}
\hat{N}_{k}=\left\{\hat{w}+\hat{w}_{k} \mid \hat{w} \in \hat{L}_{k+1}, \hat{w}+\hat{w}_{k} \leq \bar{C}\right\} . \tag{26}
\end{equation*}
$$

According to the dominance principle, all $\hat{w} \in \hat{L}_{k+1} \cup \hat{N}_{k}$ obtained by construction, such that there exists a $\hat{w}^{\prime} \in \hat{L}_{k+1} \cup \hat{N}_{k}$, which satisfies: $\hat{w}=\hat{w}^{\prime}$, must not belong to a list $\hat{L}_{k}$. In this case, we usually say that $\hat{w}^{\prime}$ dominates the weight $\hat{w}$. Thus, we can define the set $\hat{D}_{k}$ of dominated weights at stage $k$ as follows:

$$
\hat{D}_{k}=\left\{\hat{w} \mid \hat{w} \in \hat{L}_{k+1} \cup \hat{N}_{k}, \exists \hat{w}^{\prime} \in \hat{L}_{k+1} \cup \hat{N}_{k} \text { with } \hat{w}=\hat{w}^{\prime}\right\} .
$$

As a consequence, for all positive integers $k$, the dynamic programming recursive list $\hat{L}_{k}$ is denned as follows:

$$
\begin{equation*}
\hat{L}_{k}=\hat{L}_{k+1} \cup \hat{N}_{k}-\hat{D}_{k} \tag{27}
\end{equation*}
$$

Note that the lists $\hat{L}_{k}$ are organised as sets of monotonically increasing weights.
From the lists $L_{n-1}$ and $\hat{L}_{k}$, we can derive the value $\hat{w}_{k-1}, k=n, n-1, \ldots, 3$, according to Equation (16) with:

$$
v(k-1)=\max \left\{\begin{array}{l}
w+\hat{w} \mid w+\hat{w} \leq C-w_{k-1}, \hat{w} \in \hat{L}_{k}  \tag{28}\\
\text { and }(w, p) \in L_{n-1}, \text { with } p \leq k-2
\end{array}\right\} .
$$

From the list $\hat{L}_{2}$, we can compute the value of $\hat{w}_{1}$ according to Equation (18) with:

$$
\begin{equation*}
v(1)=\max \left\{\hat{w} \mid \hat{w} \leq C-w_{1}, \hat{w} \in \hat{L}_{2}\right\} . \tag{29}
\end{equation*}
$$

Remark 2. Similarly to Step 1, only one list is stored in the memory during Step 2, i.e., the current list $\hat{L}_{k}$. As a consequence, the Step 2 space complexity is $\mathcal{O}(\bar{C})$. The computation of $v(k-1)$ is performed by merging the lists $L_{n-1}$ and $\hat{L}_{k}$ with time comlexity $\mathcal{O}(\bar{C})$; i.e., the ordered lists $L_{n-1}$ and $\hat{L}_{k}$ are simultaneously examined once. The former list is examined in an increasing way; the latter in a decreasing way (see Ahrens and Finke (1975)). Note also that each list $L_{k}$ is generated with time complexity $\mathcal{O}(\bar{C})$. Thus, the Step 2 time complexity is $\mathcal{O}(n \bar{C})$. As a result, the time complexity of the global method is $\mathcal{O}(n \bar{C})$ and the space complexity is $\mathcal{O}(\bar{C})$. We recall that the time and space complexities of Kianfar's method are $\mathcal{O}\left(n^{2} C\right)$ and $\mathcal{O}(n C)$ respectively (see Kianfar, 1971; Kianfar, 1976).

In order to illustrate our algorithm, we now display a simple example. Let us consider the following constraint:

$$
\begin{equation*}
5 x_{1}+11 x_{2}+3 x_{3}+6 x_{4} \leq 12 \tag{30}
\end{equation*}
$$

We note that the associated hyperplane passes through no point with integer components.

$$
\text { We have: } \bar{C}=12-3=9
$$

Step 1

$$
\begin{aligned}
& L_{0}=\{(0,0)\} . \\
& L_{1}=\{(0,0),(5,1)\} . L_{2}=\{(0,0),(5,1)\} . \\
& L_{3}=\{(0,0),(3,3),(5,1)(8,3)\} . \\
& C-w_{4}=12-6=6 .
\end{aligned}
$$

Using Equation (23), we have: $v(4)=\max \left\{w \mid w<6,(w, p) \in L_{3}\right\}$. Thus, $v(4)=5$.

$$
\hat{w}_{4}=C-v(4)=12-5=7 .
$$

Step 2

$$
\begin{aligned}
& \hat{L}_{5}=\{0\} \\
& \hat{L}_{4}=\{0,7\} . \\
& C-w_{3}=12-3=9
\end{aligned}
$$

Using Equation (28), we have: $v(3)=\max \left\{w+\hat{w} \mid w+\hat{w} \leq 9, \hat{w} \in \hat{L}_{4}\right.$ and $(w, p) \in L_{3}$, with $p<2\}$. Thus, $v(3)=7$.

$$
\begin{aligned}
& \hat{w}_{3}=C-v(3)=12-7=5 . \\
& \hat{L}_{3}=\{0,5,7\} . \\
& C-w_{2}=12-11=1 .
\end{aligned}
$$

We can compute $v(2)$ as shown above. We obtain: $v(2)=0$.

$$
\begin{aligned}
& \hat{w}_{2}=C-v(2)=12-0=12 . \\
& \hat{L}_{2}=\{0,5,7\} . \\
& C-w_{1}=12-5=7 .
\end{aligned}
$$

Using Equation (29), we have: $v(1)=7$.

$$
\hat{w}_{1}=C-v(1)=12-7=5 .
$$

Thus, after constraint rotation, we obtain the following new constraint:

$$
\begin{equation*}
5 x_{1}+12 x_{2}+5 x_{3}+7 x_{4} \leq 12 \tag{31}
\end{equation*}
$$

note that the associated new hyperplane now passes through the following three points with integer components: $(1,0,0,1),(0,1,0,0),(0,0,1,1)$.

## 3 Conclusion

In this paper, we have proposed a significant improvement for constraint rotation algorithms. The time and space complexities of the revisited algorithm we propose are $\mathcal{O}(n \bar{C})$ and $\mathcal{O}(\bar{C})$, respectively, where $n$ denotes the number of variables and $\bar{C}$ is smaller than the capacity of the knapsack.

Finally, we also note that the constraint rotation algorithm proposed in this paper lends itself very well to parallel computing. As a matter of fact, the different constraints can be treated independently via several processors. Moreover, the
dynamic programming lists method used in Steps 1 and 2 are also well suited to parallel computing (see El Baz and Elkihel (2005)); this permits one to obtain a $\mathcal{O}\left(\frac{n C}{q}\right)$ time complexity, where $q$ denotes the number of processors.

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