# On LP-based approximation for copositive formulation of stable set problem 

Katsuya Tono ${ }^{1}$<br>${ }^{1}$ Graduate School of Information Science and Technology, The University of Tokyo, Bunkyo-ku, Tokyo 113-8656, Japan<br>E-mail katsuya_tono@mist.i.u-tokyo.ac.jp

Received July 24, 2015, Accepted October 7, 2015


#### Abstract

De Klerk-Pasechnik (2002) showed a way to compute the stability number $\alpha(G)$ via copositive programming and proposed LP- and SDP-based approximation schemes for the copositive program. In this paper, we show that their LP-based approximation for the stable set problem is equivalent to a problem of minimizing a quadratic form over a rational grid on the simplex, which can be viewed as a discretized version of the Motzkin-Straus theorem. Furthermore, we provide an algorithm to recover a maximum stable set from an optimal solution of the LPbased approximation and propose a simple local search heuristics for the stable set problem.


Keywords stable set problem, linear programming, copositive programming, MotzkinStraus theorem, heuristics
Research Activity Group Discrete Systems

## 1. Introduction

The stable set problem is a classical problem in combinatorial optimization, which has important applications in various fields. A pioneering work by Lovász [1] introduced an SDP relaxation for the stable set problem to obtain an upper bound $\theta(G)$ (called theta number) of the stability number $\alpha(G)$. De Klerk-Pasechnik [2] refined this approach and provided a way to obtain $\alpha(G)$ via copositive programming. They also provided LPand SDP-based approximation schemes by replacing the copositive cone $\mathcal{C}_{n}$ with a sequence of cones that converges to $\mathcal{C}_{n}$ and proved that both of the schemes yield $\alpha(G)$ after rounding down if the degree $r$ of approximation is sufficiently large.

In this paper, we establish a new explicit formula for the optimal value of their LP-based approximation and reformulate it as a minimization of a quadratic form over a rational grid on the simplex. Our reformulation sheds a new insight on the LP-based approximation and clarifies its power of approximation. Our discrete quadratic program may be viewed as a discretized version of a classical result by Motzkin-Straus [3] on representing the stability number as a quadratic program. We provide an algorithm to recover a stable set from the support of a feasible solution. Our algorithm actually gives a maximum stable set from any optimal solution, provided the degree $r$ of approximation is at least $\alpha(G)-2$. This lower bound sharpens the result of Peña-Vera-Zuluaga [4]. Furthermore, on the basis of these results, we provide a quite simple local search heuristics for the stable set problem. The efficiency of the proposed heuristics is confirmed by computational experiments on DIMACS benchmarks.

## 2. Preliminaries

### 2.1 Stable set problem

Throughout the paper $G=(V, E)$ will denote a simple undirected graph with vertex set $V=\{1, \ldots, n\}$ and edge set $E$. Also, let $A$ be the adjacency matrix of $G, I$ the $n \times n$ identity matrix, and $e$ the $n$-dimensional allone vector. A subset $V^{\prime} \subseteq V$ is stable if $\{i, j\} \notin E$ for all $i, j \in V^{\prime}$. A stable set is maximum if there are no larger stable sets in $G$ and the stability number $\alpha(G)$ is the cardinality of a maximum stable set in $G$. The stable set problem is to find a maximum stable set and is known to be NP-hard [5].

### 2.2 Copositive programming

Let $\mathcal{S}_{n}$ be the set of all $n \times n$ real symmetric matrices. A matrix $X \in \mathcal{S}_{n}$ is said to be copositive if $y^{\top} X y$ is nonnegative for all $n$-dimensional nonnegative vectors $y \in \mathbb{R}_{+}^{n}$. The set of all $n \times n$ copositive matrices is denoted by $\mathcal{C}_{n}$. A Copositive program is a convex optimization problem of the following form:

$$
\begin{array}{ll}
\text { Minimize } & \operatorname{Tr}(C X) \\
\text { subject to } & \operatorname{Tr}\left(A_{i} X\right)=b_{i} \quad(i=1, \ldots, m), \quad X \in \mathcal{C}_{n}
\end{array}
$$

where $A_{i}, X, C \in \mathbb{R}^{n \times n}$ and $b_{i} \in \mathbb{R}$. The stability number $\alpha(G)$ can be obtained by solving a copositive program.
Theorem 1 (De Klerk-Pasechnik [2]) The stability number $\alpha(G)$ equals the optimal value of

$$
\begin{array}{ll}
\text { Minimize } & \lambda \\
\text { subject to } & \lambda(I+A)-e e^{\top} \in \mathcal{C}_{n}, \quad \lambda \in \mathbb{R} . \tag{1}
\end{array}
$$

Theorem 1 implies that copositive programming is intractable. In fact, determining whether a matrix is copositive is co-NP-complete [6].

### 2.3 LP-based approximation

De Klerk-Pasechnik [2] introduced an LP-based approximation hierarchy for $\mathcal{C}_{n}$. We consider the equivalent definition of copositivity to construct the approximate cone. We can see that $M \in \mathcal{S}_{n}$ is copositive if and only if the fourth order form given by

$$
P_{M}(x)=(x \circ x)^{\top} M(x \circ x)=\sum_{i, j=1}^{n} M_{i j} x_{i}^{2} x_{j}^{2}
$$

is nonnegative, where " $\circ$ " indicates the componentwise product. Obviously, a sufficient condition for $M$ to be copositive is that all the coefficients of $P_{M}(x)$ are nonnegative. Then higher-order sufficient conditions can be derived by considering whether the coefficients of the polynomial

$$
P_{M}^{(r)}(x)=\left(\sum_{i, j=1}^{n} M_{i j} x_{i}^{2} x_{j}^{2}\right)\left(\sum_{i=1}^{n} x_{i}^{2}\right)^{r}
$$

take nonnegative values. For any integer $r \geq 0$, we define $\mathcal{C}_{n}^{r}$ as the cone of matrices $M \in \mathcal{S}_{n}$ such that all the coefficients of $P_{M}^{(r)}(x)$ are nonnegative. Then the following inclusions hold:

$$
\begin{equation*}
\mathcal{C}_{n}^{0} \subseteq \mathcal{C}_{n}^{1} \subseteq \cdots \subseteq \mathcal{C}_{n} \tag{2}
\end{equation*}
$$

We define $\zeta^{(r)}(G)$ as the minimum of the LP-based approximation of (1):

$$
\begin{array}{ll}
\text { Minimize } & \lambda \\
\text { subject to } & \lambda(I+A)-e e^{\top} \in \mathcal{C}_{n}^{r}, \quad \lambda \in \mathbb{R}, \tag{3}
\end{array}
$$

where we set $\zeta^{(r)}(G)=\infty$ if the problem is infeasible. Then it follows from (2) that

$$
\zeta^{(0)}(G) \geq \zeta^{(1)}(G) \geq \cdots \geq \alpha(G)
$$

De Klerk-Pasechnik [2] showed that $\left\lfloor\zeta^{(r)}(G)\right\rfloor=\alpha(G)$ if $r \geq \alpha(G)^{2}$. Peña-Vera-Zuluaga [4] strengthened and sharpened their result as follows.
Theorem 2 (Peña-Vera-Zuluaga [4]) It holds that $\left\lfloor\zeta^{(r)}(G)\right\rfloor=\alpha(G)$ if and only if $r \geq \alpha(G)^{2}-1$. Furthermore, $\zeta^{(r)}(G)<\infty$ if and only if $r \geq \alpha(G)-1$.
Thus we can regard problem (3) as an LP-based formulation of the stable set problem for sufficiently large $r$.

## 3. Results

### 3.1 Discrete version of Motzkin-Straus theorem

We present a new explicit expression of $\zeta^{(r)}(G)$ as follows.
Theorem 3 For $r \geq \alpha(G)-1$, we have

$$
\begin{equation*}
\zeta^{(r)}(G)=\max _{w \in I_{n}(r+2)} \frac{(r+2)(r+1)}{w^{\top}(I+A) w-(r+2)} \tag{4}
\end{equation*}
$$

where

$$
I_{n}(t)=\left\{w \in \mathbb{Z}_{+}^{n} \mid e^{\top} w=t\right\}
$$

Considering (3) as an LP with a single variable $\lambda$, we can solve it easily by deriving conditions for each coefficient of $P_{M}^{(r)}(x)$ to be nonnegative. We can calculate them by expanding the polynomial.

Lemma 4 (Bomze-de Klerk [7]) Let $M \in \mathcal{S}^{n}$ and introduce the multinomial coefficients

$$
c(m)=\frac{\left(\sum_{i=1}^{n} m_{i}\right)!}{m_{1}!\ldots m_{n}!}
$$

for any $m \in \mathbb{Z}_{+}^{n}$. Then we have

$$
P_{M}^{(r)}(x)=\sum_{w \in I_{n}(r+2)} a_{w} x_{1}^{w_{1}} \ldots x_{n}^{w_{n}}
$$

where

$$
\begin{aligned}
& a_{w}=\frac{c(w)}{(r+2)(r+1)}\left(w^{\top} M w-w^{\top} \operatorname{diag} M\right), \\
& \operatorname{diag} M=\left(M_{11}, \ldots, M_{n n}\right)^{\top} .
\end{aligned}
$$

Now we can obtain (4) immediately from Lemma 4.
Proof of Theorem 3 The constraint in Problem (3), $\lambda(I+A)-e e^{\top} \in \mathcal{C}_{n}^{r}$, means that every coefficient of $P_{\lambda(I+A)-e e^{\top}}^{r}(x)$ is nonnegative. By Lemma 4, this is equivalent to

$$
\begin{aligned}
w^{\top} & \left(\lambda(I+A)-e e^{\top}\right) w-w^{\top} \operatorname{diag}\left(\lambda(I+A)-e e^{\top}\right) \\
& =\lambda w^{\top}(I+A) w-\left(e^{\top} w\right)^{2}-(\lambda-1) w^{\top} e \\
& =\lambda w^{\top}(I+A) w-(r+2)^{2}-(\lambda-1)(r+2) \\
& =\lambda\left[w^{\top}(I+A) w-(r+2)\right]-(r+2)(r+1) \geq 0
\end{aligned}
$$

for every $w \in I_{n}(r+2)$. If $r \geq \alpha(G)-1$, we have $w^{\top}(I+$ A) $w-(r+2)>0$ for every $w \in I_{n}(r+2)$ from Theorem 2 . Therefore (4) holds.
(QED)
Our formula can be viewed as a discretized version of the Motzkin-Straus formula.
Theorem 5 (Motzkin-Straus [3]) We have

$$
\begin{equation*}
\alpha(G)=\max _{x \in \Delta} \frac{1}{x^{\top}(I+A) x} \tag{5}
\end{equation*}
$$

where $\Delta$ denotes the $n$-dimensional standard simplex. Moreover, let $\{1, \ldots, k\}$ be a maximum stable set of $G$. Then $x_{1}=\cdots=x_{k}=1 / k, x_{k+1}=\cdots=x_{n}=0$ is an optimal solution of (5).
The relation between (4) and (5) becomes more explicit if we rewrite $\zeta^{\left(r^{\prime}-2\right)}(G)$ for $r^{\prime} \geq \alpha(G)+1$ as

$$
\zeta^{\left(r^{\prime}-2\right)}(G)=\max _{x \in \Delta\left(r^{\prime}\right)} \frac{r^{\prime}-1}{r^{\prime} x^{\top}(I+A) x-1}
$$

where $\Delta\left(r^{\prime}\right)$ denotes the set of $1 / r^{\prime}$-integral vectors in $\Delta$ for $r^{\prime} \in \mathbb{N}$. Theorem 5 also states that the support of an optimal solution of (5) is a maximum stable set. Correspondingly, we can derive a maximum stable set from the support of an optimal solution of (4).

### 3.2 Recovery of stable set

We provide an algorithm to obtain a maximum stable set from the support of an arbitrary optimal solution of (4).
Definition 6 Let $e_{i}$ be the unit vector of the ith coordinate direction. We denote by $\widehat{x}$ the vector obtained from $w \in I_{n}(r+2)$ by applying the following procedure:
(i) If there are $\{i, j\} \in E$ such that $w_{i}>0, w_{j}>0$,
choose $w+w_{i}\left(e_{j}-e_{i}\right)$ or $w+w_{j}\left(e_{i}-e_{j}\right)$ as $w^{\prime}$ that makes $w^{\prime \top}(I+A) w^{\prime}$ smaller and replace $w$ with $w^{\prime}$.
(ii) Repeat (i) until the support of $w$ corresponds to a stable set of $G$.
We show that this procedure recovers a maximum stable set if $w$ is optimal. Note that it holds for $r \geq \alpha(G)-1$ that

$$
\begin{aligned}
& \underset{w \in I_{n}(r+2)}{\arg \min } w^{\top}(I+A) w \\
& \quad=\underset{w \in I_{n}(r+2)}{\arg \max } \frac{(r+2)(r+1)}{w^{\top}(I+A) w-(r+2)} .
\end{aligned}
$$

Lemma 7 It holds for any $w \in I_{n}(r+2)$ that

$$
w^{\top}(I+A) w \geq \widehat{w}^{\top}(I+A) \widehat{w} .
$$

Proof At each choice of $w^{\prime}$ in Definition 6, if $w^{\prime}=$ $w+w_{j}\left(e_{i}-e_{j}\right)$, we have

$$
\begin{aligned}
& w^{\prime \top}(I+A) w^{\prime}-w^{\top}(I+A) w \\
& \quad=w_{j}^{2}\left(I_{i i}-A_{i j}-A_{j i}+I_{j j}\right)+2 w_{j} w^{\top}(I+A)\left(e_{i}-e_{j}\right) \\
& \quad=2 w_{j} w^{\top}(I+A)\left(e_{i}-e_{j}\right),
\end{aligned}
$$

since $\{i, j\} \in E$. Similarly, if $w^{\prime}=w+w_{i}\left(e_{j}-e_{i}\right)$, we have
$w^{\prime \top}(I+A) w^{\prime}-w^{\top}(I+A) w=2 w_{i} w^{\top}(I+A)\left(e_{j}-e_{i}\right)$.
Since one of these values are nonpositive, $w^{\top}(I+A) w \geq$ $w^{\prime \top}(I+A) w^{\prime}$. Thus we have $w^{\top}(I+A) w \geq \widehat{w}^{\top}(I+A) \widehat{w}$ by repeating the process.
(QED)
Theorem 8 Let $w^{*} \in \arg \min _{w \in I_{n}(r+2)} w^{\top}(I+A) w$ and $S(w)=\left\{i \mid w_{i} \neq 0\right\}$. Then $S\left(\widehat{w}^{*}\right)$ is a maximum stable set if and only if $r \geq \alpha(G)-2$.
Proof If $r<\alpha(G)-2$, it follows from the definition of $I_{n}(r+2)$ that $\left|S\left(\widehat{w}^{*}\right)\right|<\alpha(G)$, which implies that $S\left(\widehat{w}^{*}\right)$ is not a maximum stable set.

To show the sufficiency, suppose $\left|S\left(\widehat{w}^{*}\right)\right|<\alpha(G)$. Then there exists $k \notin S\left(\widehat{w}^{*}\right)$ such that $S\left(\widehat{w}^{*}\right) \cup\{k\}$ is a stable set and $l \in S\left(\widehat{w}^{*}\right)$ such that $\widehat{w}_{l}^{*} \geq 2$. We consider the vector $\tilde{w}^{*}-e_{l}+e_{k} \in I_{n}(r+2)$. It follows from the stability of $S\left(\widehat{w}^{*}\right)$ and $S\left(\widehat{w}^{*}-e_{l}+e_{k}\right)$ that

$$
\begin{aligned}
& \widehat{w}^{* \top}(I+A) \widehat{w}^{*}-\left(\widehat{w}^{*}-e_{l}+e_{k}\right)^{\top}(I+A)\left(\widehat{w}^{*}-e_{l}+e_{k}\right) \\
& \quad=\widehat{w}^{* \top} \widehat{w}^{*}-\left(\widehat{w}^{*}-e_{l}+e_{k}\right)^{\top}\left(\widehat{w}^{*}-e_{l}+e_{k}\right) \\
& \quad=2\left(\widehat{w}_{l}^{*}-1\right)>0 .
\end{aligned}
$$

Now, from the optimality of $w^{*}$ and Lemma 7,

$$
\begin{aligned}
w^{*}(I+A) w^{*} & =\widehat{w}^{* \top}(I+A) \widehat{w}^{*} \\
& >\left(\widehat{w}^{*}-e_{l}+e_{k}\right)^{\top}(I+A)\left(\widehat{w}^{*}-e_{l}+e_{k}\right) .
\end{aligned}
$$

This contradicts $w^{*} \in \arg \min _{w \in I_{n}(r+2)} w^{\top}(I+A) w$. By contradiction, $\left|S\left(\widehat{w}^{*}\right)\right|=\alpha(G)$.
(QED)
Thus we can solve the stable set problem by minimizing the quadratic form over $I_{n}(r+2)$ for $r \geq \alpha(G)-2$, although $\left\lfloor\zeta^{(r)}(G)\right\rfloor \neq \alpha(G)$ if $\alpha(G) \leq r<\alpha(G)^{2}-1$. Since we need $r^{\prime} \geq \alpha(G)^{2}-1$ to obtain $\alpha(G)$ in (4),

```
Algorithm 1 Local search for the stable set problem
    \(w:=e\)
    while \(w\) is not a local optimum do
        choose \(w^{\prime} \in N(w)\)
        if \(w^{\prime \top}(I+A) w^{\prime} \leq w^{\top}(I+A) w\) then
                \(w:=w^{\prime}\)
        end if
    end while
    compute \(\widehat{w}\)
    return \(S(\widehat{w})\)
```

Theorem 8 sharpens Theorem 2 with regard to the degree of approximation.

### 3.3 Local search heuristics

We propose a simple heuristics for the stable set problem using the results in the previous subsections. For each $w \in I_{n}(r+2)$, we regard

$$
N(w)=\left\{w+e_{i}-e_{j} \mid i, j \in\{1, \ldots, r\}, w_{j}>0\right\}
$$

as a neighborhood of $w$. This neighborhood leads to a local search shown in Algorithm 1. The heuristic starts from the initial point $w=e$, which implies that we set $r=n-2$. Then we repeatedly pick $w^{\prime} \in N(w)$ to get the objective value smaller until $w$ reaches a local optimum. In the algorithm, we take $w$ as a local optimum if the objective value does not change after $n$ updates of $w$. Finally, we compute $\widehat{w}$ and its support $S(\widehat{w})$.

The performance of this heuristics has been tested on the complement graphs of the DIMACS clique benchmarks. See for details of the graphs at

## http://dimacs.rutgers.edu/Challenges/.

We applied the heuristics 10 times for each graph. All computations were executed with 2.4 GHz Intel CPU Core i7 and 16 GB of memory. The results are given in Table 1. The columns "Name", " $\alpha(\bar{G})$ ", "Solution", "Average", and "Time" represent the name of the graph, the stability number of the complement graph, the maximum cardinality of the stable sets obtained, the average cardinality of them, and CPU time in seconds.

The proposed heuristics found a maximum stable set in 24 of the 36 instances in the categories of CFAT, Johnson, Hamming, PHAT, and MANN. However, it did not perform well on the graphs in the categories of Keller, SAN, SANR, and BROCK.

## 4. Conclusion

In this paper, we have reformulated the LP-based approximation for the stable set problem as a discrete version of the Motzkin-Straus theorem. This reformulation leads to a procedure to obtain a maximum stable set from an optimal solution and a local search heuristics for the stable set problem. Furthermore, we showed the strict lower bound for our procedure to yield a maximum stable set. This lower bound is less than the strict bound to compute $\alpha(G)$ as the optimal value of the LP-based approximation.

It remains as a future work to investigate whether we can apply a similar idea to other problems in combinato-

Table 1. Results on the DIMACS benchmarks.

| Name | $\alpha(\bar{G})$ | Solution | Average | Time (s) |
| :---: | :---: | :---: | :---: | :---: |
| c-fat200-1 | 12 | 12 | 12.0 | 0.5 |
| c-fat200-2 | 24 | 24 | 23.0 | 0.2 |
| c-fat200-5 | 58 | 58 | 55.2 | 0.1 |
| c-fat500-1 | 14 | 14 | 13.4 | 4.6 |
| c-fat500-2 | 26 | 26 | 26.0 | 2.0 |
| c-fat500-5 | 64 | 64 | 64.0 | 0.8 |
| c-fat500-10 | $\geq 126$ | 126 | 125.8 | 0.5 |
| johnson8-2-4 | 4 | 4 | 2.6 | <0.1 |
| johnson8-4-4 | 14 | 14 | 12.0 | 0.1 |
| johnson16-2-4 | 8 | 8 | 7.7 | 0.2 |
| johnson32-2-4 | 16 | 16 | 15.7 | 3.6 |
| keller4 | 11 | 9 | 8.0 | 0.3 |
| keller5 | 27 | 19 | 17.3 | 5.5 |
| keller6 | $\geq 59$ | 38 | 35.8 | 125.4 |
| hamming6-2 | 32 | 32 | 28.1 | <0.1 |
| hamming6-4 | 4 | 4 | 2.4 | <0.1 |
| hamming8-2 | 128 | 128 | 119.0 | 0.1 |
| hamming8-4 | 16 | 16 | 14.0 | 0.8 |
| hamming10-2 | 512 | 512 | 442.0 | 1.6 |
| hamming10-4 | $\geq 40$ | 34 | 31.2 | 9.9 |
| san200_0.7_1 | 30 | 15 | 15.0 | $<0.1$ |
| san200_0.7_2 | 18 | 12 | 12.0 | <0.1 |
| san200_0.9_1 | 70 | 45 | 45.0 | $<0.1$ |
| san200_0.9_2 | 60 | 38 | 36.1 | 0.1 |
| san200_0.9_3 | 44 | 33 | 31.4 | 0.1 |
| san400_0.5_1 | 13 | 7 | 7.0 | <0.1 |
| san400_0.7_1 | 40 | 20 | 20.0 | 0.1 |
| san400_0.7_2 | 30 | 15 | 15.0 | 0.1 |
| san400_0.7_3 | 22 | 12 | 12.0 | 0.1 |
| san400_0.9_1 | 100 | 52 | 50.6 | 0.2 |
| san1000 | 15 | 8 | 8.0 | 0.5 |
| sanr200_0.7 | 18 | 17 | 15.2 | 0.3 |
| sanr200_0.9 | 42 | 41 | 37.4 | 0.1 |
| sanr400_0.5 | 13 | 11 | 9.9 | 4.2 |
| sanr400_0.7 | 21 | 21 | 16.3 | 1.6 |
| brock200_1 | 21 | 19 | 17.0 | 0.3 |
| brock200_2 | 12 | 9 | 7.7 | 0.6 |
| brock200_3 | 15 | 13 | 11.2 | 0.5 |
| brock200_4 | 17 | 15 | 13.1 | 0.3 |
| brock400_1 | 27 | 22 | 20.4 | 1.4 |
| brock400_2 | 29 | 22 | 20.2 | 1.3 |
| brock400_3 | 31 | 22 | 19.6 | 1.5 |
| brock400_4 | 33 | 24 | 20.3 | 1.3 |
| brock800_1 | 23 | 18 | 16.1 | 15.3 |
| brock800_2 | 24 | 18 | 16.2 | 14.9 |
| brock800_3 | 25 | 18 | 16.4 | 15.6 |
| brock800_4 | 26 | 19 | 16.7 | 19.3 |
| p_hat300-1 | 8 | 7 | 6.0 | 3.2 |
| p_hat300-2 | 25 | 25 | 23.5 | 0.6 |
| p_hat300-3 | 36 | 36 | 31.8 | 0.4 |
| p_hat500-1 | 9 | 8 | 6.8 | 10.0 |
| p_hat500-2 | 36 | 36 | 34.4 | 1.2 |
| p_hat500-3 | $\geq 49$ | 49 | 47.2 | 0.9 |
| p_hat700-1 | 11 | 9 | 6.7 | 25.2 |
| p_hat700-2 | 44 | 44 | 41.8 | 2.8 |
| p_hat700-3 | 62 | 60 | 58.4 | 1.8 |
| p_hat1000-1 | 10 | 10 | 7.1 | 56.7 |
| p_hat1000-2 | 46 | 45 | 42.9 | 6.8 |
| p_hat1000-3 | 65 | 64 | 61.6 | 4.1 |
| p_hat1500-1 | 12 | 11 | 7.7 | 186.1 |
| p_hat1500-2 | 63 | 63 | 60.7 | 13.4 |
| p_hat1500-3 | 94 | 90 | 87.5 | 8.8 |
| MANN_a9 | 16 | 16 | 14.7 | <0.1 |
| MANN_a27 | 126 | 118 | 117.2 | 0.1 |
| MANN_a45 | 345 | 332 | 330.4 | 0.5 |
| MANN_a81 | $\geq 1100$ | 1081 | 1080.2 | 5.8 |

rial optimization which can be formulated as a copositive program. Also, the performance of our heuristics can be expected to improve by using a more efficient technique, such as tabu search, for the local search.

## Acknowledgments

The author would like to thank Hiroshi Hirai for his careful reading and helpful comments. This research was supported by JSPS KAKENHI Grant Number 26330023 and JST, ERATO, Kawarabayashi Large Graph Project.

## References

[1] L. Lovász, On the Shannon capacity of a graph, IEEE Trans. Inf. Theory, 25 (1979), 1-7.
[2] E. de Klerk and D. V. Pasechnik, Approximation of the stability number of a graph via copositive programming, SIAM J. Optimiz., 12 (2002), 875-892.
[3] T. S. Motzkin and E. G. Straus, Maxima for graphs and a new proof of a theorem of Turán, Can. J. Math., $\mathbf{1 7}$ (1965), 533-540.
[4] J. Peña, J. Vera and L. F. Zuluaga, Computing the stability number of a graph via linear and semidefinite programming, SIAM J. Optimiz., 18 (2007), 87-105.
[5] R. M. Karp, Reducibility among combinatorial problems, in: Proc. of Complexity of Computer Computations, R. E. Miller and J. W. Thatcher ed., The IBM Research Symposia Series, pp. 85-103, Plenum Press, New York, 1972.
[6] K. G. Murty and S. N. Kabadi, Some NP-complete problems in quadratic and linear programming, Math. Program., 39 (1987), 117-129.
[7] I. M. Bomze and E. de Klerk, Solving standard quadratic optimization problems via linear, semidefinite and copositive programming, J. Global Optim., 24 (2002), 163-185.

