Appendix of Local Search for Integer Quadratic Programming

Anonymous submission

Appendix A: Detailed Calculation of Inequality Exploration Move Operator

In this section, we discuss the inequality exploration in different situations. For any $x_j \in \mathcal{S}$ and its associated constraint:

$$con_i = H(i, x_j) \cdot x_j + I(i, x_j) \le c_i.$$

$$\Theta(x_j) = W \cdot x_j^2 + K(x_j) \cdot x_j.$$

$$\xi = \frac{K(x_j)}{-2W}$$

The feasible domain of x_i in con_i is denoted as \mathcal{D} , \mathcal{D} is :

$$\mathcal{D} = \begin{cases} [x_0, +\infty] & \text{if } A = 0, \alpha(H(I, x_j)) < 0, \\ [-\infty, x_0] & \text{if } A = 0, \alpha(H(I, x_j)) > 0, \\ [x_1, x_2] & \text{if } A > 0, \Delta \neq 0 \\ [-\infty, x_1] \cup [x_2, +\infty] & \text{if } A < 0, \Delta \neq 0, \end{cases}$$

We determine a candidate value x^{\min} based on the specified conditions \cos_i and $\theta(x_j)$, where x^{\min} is the value in $\mathcal D$ that minimizes $\Theta(x)$ (more detailed calculations of x^{\min} are provided in the appendix). This candidate value x^{\min} is then used to find the nearest feasible integer within the domain $\mathcal D$ to apply the $iem(x_j, \cos_i, \alpha)$ operator. Specifically, x^{\min} is calculated by these four forms of:

I. Linear constraint, Linear objective function

If con_i is a Linear constraint with $\alpha(H(I, x_j)) = 0$ and $\Theta(x_j)$ is a linear objective function with W = 0. x_{min} is:

$$x_{min} = \begin{cases} x_0, & \text{if } D = [x_0, +\infty], \alpha(K(I, x_j)) < 0\\ x_0, & \text{if } D = [-\infty, x_0], \alpha(K(I, x_j)) < 0\\ \alpha(x_j), & \text{otherwise.} \end{cases}$$
(2)

II. Quadratic constraint, Linear objective function

If con_i is a Quadratic constraint with $\alpha(H(I, x_j)) \neq 0$ and $\Theta(x_j)$ is a linear objective function with W = 0. x_{min} is:

$$x_{min} = \begin{cases} x_2, & \text{if } D = [x_1, x_2] \text{ and } \alpha(K(I, x_j)) < 0, \\ x_1, & \text{if } D = [x_1, x_2] \text{ and } \alpha(K(I, x_j)) > 0, \\ \alpha(x_j), & \text{otherwise.} \end{cases}$$
(3)

III. Linear constraint, Quadratic objective function

If con_i is a Linear constraint with $\alpha(H(I,x_j))=0$ and $\Theta(x_j)$ is a Quadratic objective function with $W\neq 0$. x_{min} is:

$$x_{min} = \begin{cases} x_0, & \text{if } D = [x_0, +\infty], W > 0, \xi \le x_0, \\ \xi, & \text{if } D = [x_0, +\infty], W > 0, \xi > x_0, \\ \xi, & \text{if } D = [-\infty, x_0], W > 0, \xi \le x_0 \\ x_0, & \text{if } D = [-\infty, x_0], W > 0, \xi > x_0 \\ \alpha(x_j), & \text{otherwise.} \end{cases}$$
(4)

IV. Quadratic constraint, Quadratic objective function

if $D = [x_1, x_2], x_{min}$ is

If con_i is a Quadratic constraint with $\alpha(H(I,x_j)) \neq 0$ and $\Theta(x_j)$ is a Quadratic objective function with $W \neq 0$. If $D = [-\infty, x_1] \cup [x_2, +\infty]$, x_{min} is:

$$x_{min} = \begin{cases} \xi, & \text{if } W > 0, \xi < x_1 \text{ or } \xi > x_2, \\ x_1, & \text{if } W > 0, x_1 \le \xi \le x_2, |x_1 - \xi| \le |x_2 - x_i| \\ x_2, & \text{if } W > 0, x_1 \le \xi \le x_2, |x_1 - \xi| > |x_2 - x_i| \\ \alpha(x_j), & \text{otherwise.} \end{cases}$$

$$(5)$$

$$x_{min} = \begin{cases} x_1, & \text{if } W > 0, \xi < x_1 \\ x_2, & \text{if } W > 0, \xi > x_1 \\ \xi, & \text{if } W > 0, x_1 \leq \xi \leq x_2 \\ x_1, & \text{if } W < 0, x_1 \leq \xi \leq x_2, |x_1 - \xi| > |x_2 - x_i| \\ x_2, & \text{if } W < 0, x_1 \leq \xi \leq x_2, |x_1 - \xi| \leq |x_2 - x_i| \\ x_1, & \text{if } W < 0, \xi > x_2 \\ x_2, & \text{if } W < 0, \xi < x_1 \\ \alpha(x_j), & \text{otherwise.} \end{cases}$$

(6)

Appendix B: Complete results of Sensitivity analysis on the parameters

The complete results of the Sensitivity analysis on the parameters:

Table 1: Results of LS-IQCQP under different parameter settings. P12 is the parameters ultimately used by LS-IQCQP.

Parameter	,		Total	Total	Total
settings	t	ζ	#win (10s)		#win (300s)
P0	50	50	175	177	180
P1	50	80	177	174	178
P2	50	100	177	176	177
P3	50	200	173	173	180
P4	50	300	172	180	176
P5	80	50	178	171	179
P6	80	80	174	177	174
P7	80	100	180	178	182
P8	80	200	174	171	175
P9	80	300	175	178	178
P10	100	50	174	177	178
P11	100	80	180	180	180
P12	100	100	177	176	178
P13	100	200	178	174	175
P14	100	300	173	180	177
P15	200	50	179	179	177
P16	200	80	177	171	176
P17	200	100	179	175	176
P18	200	200	178	174	175
P19	200	300	172	177	174
P20	300	50	177	176	177
P21	300	80	179	177	178
P22	300	100	178	180	176
P23	300	200	179	175	178
P24	300	300	174	176	177