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# Reduced RLT constraints for polynomial programming 

Sonia Cafieri<br>Pierre Hansen<br>Lucas Létocart<br>Leo Liberti<br>Frédéric Messine


#### Abstract

An extension of the reduced Reformulation-Linearization Technique constraints from quadratic to general polynomial programming problems with linear equality constraints is presented and a strategy to improve the associated convex relaxation is proposed.


## 1. Introduction

Reduced RLT constraints (rRLT) are a special class of Reformulation-Linearization Technique (RLT) constraints, that apply to nonconvex (both continuous and mixed-integer) quadratic programming problems subject to linear equality constraints [2, 4, 3]. rRLT are obtained by replacing some of the quadratic terms with suitable linear constraints. These turn out to be a subset of the RLT constraints for quadratic programming [7].

We present an extension of the rRLT theory to the case of general polynomial programs. Then, we show a strategy to choose the basis of a matrix involved in the rRLT constraints generation so as to tighten the bound of the associated convex relaxation. This allows to improve the performance of a spatial Branch-and-Bound algorithm applied to nonconvex NLP and MINLP problems where such convex relaxation is computed at each node.

## 2. Extending rRLT to polynomial programs

Let $n$ be the number of variables, $q$ the degree of the polynomials in the targeted problem and $\mathcal{N}=\{1, \ldots, n\}, Q=\{2, \ldots, q\}$. For each monomial $x_{j_{1}} \cdots x_{j_{p}}, p \in Q$, appearing in the problem, we define a finite sequence $J=\left(j_{1}, \ldots, j_{p}\right)$ and consider defining constraints of the following form:

$$
\begin{equation*}
w_{J}=\prod_{\ell \leq|J|} x_{j_{\ell}} \tag{2.1}
\end{equation*}
$$

(for $|J|=1$, i.e. $J=(j)$, we also define $w_{J}=x_{j}$ ). For all $p \in Q, J \in \mathcal{N}^{p}$ and any permutation $\pi$ in the symmetric group $S_{p}$ we have that $w_{J}=w_{\pi J}$ by commutativity. We therefore define an equivalence relation $\sim$ on $\mathcal{N}^{p}$ stating that for $J, K \in \mathcal{N}^{p}, J \sim K$ only if $\exists \pi \in S_{p}$ such that $J=\pi K$. We then consider the index tuple set $\overline{\mathcal{N}}^{p}=\mathcal{N}^{p} / \sim$ to quantify over when indexing variables $w_{J}$.

We multiply the original linear constraints $A x=b$ by all monomials $\prod_{\ell \leq p-1} x_{j_{\ell}}$ and replace them by the corresponding added variables $w_{\left(J^{\prime}, j\right)}$, where $J^{\prime} \in \overline{\mathcal{N}}^{p-1}$. This yields the following rRLTS:

$$
\begin{equation*}
\forall p \in Q, J^{\prime} \in \overline{\mathcal{N}}^{p-1} \quad A \mathbf{w}_{J^{\prime}}=b w_{J^{\prime}} \tag{2.2}
\end{equation*}
$$

where $\mathbf{w}_{J^{\prime}}=\left(w_{\left(J^{\prime}, 1\right)}, \ldots, w_{\left(J^{\prime}, n\right)}\right)$. We then consider the companion system:

$$
\begin{equation*}
\forall p \in Q, J^{\prime} \in \overline{\mathcal{N}}^{p-1} \quad A \mathbf{z}_{J^{\prime}}=0 \tag{2.3}
\end{equation*}
$$

Since (2.3) is a linear homogeneous system, there is a matrix $M$ such that the companion system is equivalent to $M z=0$, the columns of which are indexed by sequences in $\overline{\mathcal{N}}^{p}$. We let $B \subseteq \overline{\mathcal{N}}^{p}$

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and $N \subseteq \overline{\mathcal{N}}^{p}$ be index sets for basic and nonbasic columns of $M$. We define the following sets:

$$
\begin{aligned}
C= & \left\{(x, w) \mid A x=b \wedge \forall p \in Q, J \in \overline{\mathcal{N}}^{p}\left(w_{J}=\prod_{\ell \leq|J|} x_{j_{\ell}}\right)\right\} \\
R_{N}= & \left\{(x, w) \mid A x=b \wedge \forall p \in Q, J^{\prime} \in \overline{\mathcal{N}}^{p-1}\left(A \mathbf{w}_{J^{\prime}}=b w_{J^{\prime}}\right) \wedge\right. \\
& \left.\forall J \in N\left(w_{J}=\prod_{\ell \leq|J|} x_{j_{\ell}}\right)\right\}
\end{aligned}
$$

Theorem 1. For each partition $B, N$ into basic and nonbasic column indices for the companion system $M z=0$, we have $C=R_{N}$.

## 3. Tightening the convex relaxation

Replacing $C$ with $R_{N}$ for some nonbasis $N$ effectively replaces some monomial terms with linear constraints, and therefore contributes to simplify the problem. A convex relaxation for the reformulated problem is readily obtained by applying monomial convexification methods in the literature $[5,6,1]$. We observe that for any given linear system there is in general more than one way to partition the variables in basics and nonbasics. Hence the set $B$ can be chosen in such a way as to decrease the discrepancy between the feasible region and its convex relaxation. Given $f: X \subseteq \mathbb{R}^{n} \rightarrow \mathbb{R}$ and the sets $S=\{(x, w) \mid w=f(x)\}$ and $\bar{S}=\{(x, w) \mid \underline{f}(x) \leq w \leq \bar{f}(x)\}$, where $\underline{f}(x), \bar{f}(x)$ are respectively a convex lower and a concave upper bounding function for $f$ (and hence $\bar{S}$ is a convex relaxation of $S$ ), the convexity gap between $S$ and $\bar{S}$ can be defined as the volume $V(S)$ of the set $\bar{S}$. Explicit expressions of $V(S)$ can be derived for a quadratic term $x_{i}^{2}$, for a bilinear term $x_{i} x_{j}$ using the Cayley-Menger formula in 3 dimensions, and for a general monomial, exploiting associativity recursively to rewrite it as product of lower degree monomials and using the preceding results.

Let $B, N$ be the basic/nonbasic sets of column indices of the companion system, which we can write as $M_{B} z_{B}+M_{N} z_{N}=0$. The elements of $B, N$ are sequences $J \in \mathscr{M}$. For $S \subseteq \mathscr{M}$ and $p \in Q$ we define $V^{S, p}=\sum_{\substack{J \in S \\|J| \mid=p}} V_{J}$ and $V^{S}=\sum_{p \in Q} V^{S, p}$. If, for all $p \in Q, V^{N, p}<V^{\beta, p}$ then the total convexity gap of $R_{N}$ is smaller than that of $C$. Thus, we aim to find $N$ such that $V^{N, p}$ is minimized, or equivalently, to find $B$ such that $V^{B, p}$ is maximized for all $p \in Q$. This yields the multi-objective problem:

$$
\left.\begin{array}{r}
\forall p \in Q \quad \max V^{B, p}  \tag{3.1}\\
M_{B} \text { is a basis of }(2.3)
\end{array}\right\}
$$

It can be shown that (3.1) is equivalent to a single-objective problem: any solution $B$ of (3.1) maximizing $V^{B}$ also maximizes $V^{B, p}$ for all $p \in Q$. In this way, we have derived a technique to choose a good basis for the companion system so as to improve the chances of tightening the lower bound of the convex relaxation associated to rRLT.

Preliminary computational experiments carried out on a set of randomly generated instances of the convex Quadratic Knapsack Problem (cQKP) show that the proposed strategy is promising in improving performances of a spatial Branch-and-Bound algorithm.

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## RRLT FOR POLYNOMIAL PROGRAMMING

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