



## Abstract

Many optimization problems reduce to the solution of a system of linear inequalities (SLI). Some solution methods use relaxed, averaged projections. Others invoke surrogate constraints (typically stemming from aggregation). This paper proposed a blend of these two approaches. A novelty comes with introducing as surrogate constrained a halfspace defined by differences of algorithmic iterates. The first iteration is identical to surrogate constraints methods. In next iterations, for a given approximation  $\bar{x}$ , besides the violated constraints in  $\bar{x}$ , we also take into consideration the surrogate inequality, which we have obtained in the previous iteration.

The motivation for this research comes from the work of H. Scolnik et al. [1], who studied some projection methods for a system of linear equations.

## 1 Introduction

We consider the problem of finding a solution  $x^*$  of a consistent system of linear inequalities

$$G^T x \leq b, \quad (1)$$

where  $G$  is a matrix of size  $n \times m$  with columns  $g_i \in \mathbb{R}^n$ ,  $i \in I = \{1, \dots, m\}$ ,  $x = (x_1, x_2, \dots, x_n)^T \in \mathbb{R}^n$ ,  $b = (b_1, b_2, \dots, b_m)^T \in \mathbb{R}^m$ .

The problem of finding a solution of a SLI is called also the *linear feasibility problem*.

Let  $\bar{x}$  be the current approximation of a solution of this problem and let  $x^+$  be the next approximation, and let  $I(\bar{x}) = \{i \in I : g_i^T \bar{x} > b_i\}$  denotes the subset of violated constraints in the point  $\bar{x}$ ,

$M = \{x \in \mathbb{R}^n : G^T x \leq b\} \neq \emptyset$  denotes the solution set of (1)  
 $M(\bar{x}) = \{x \in \mathbb{R}^n : g_i^T x \leq b_i, i \in I(\bar{x})\}$  denotes the solution set of a subsystem of violated constraints for a given approximation  $\bar{x}$  of a solution  $x^* \in M$ .

Let

$$s^i = P_i(\bar{x}) - \bar{x}, \quad (2)$$

where  $P_i$  denotes the metric projection onto the halfspace  $H_i = \{x \in \mathbb{R}^n : g_i^T x \leq b_i\}$ .

We assume, without loss of generality, that  $\|g_i\| = 1$ ,  $i \in I$ , where  $\|\cdot\|$  denotes the Euclidean norm.

Let  $w = (w_1, \dots, w_m)^T \in \Delta_m = \{u \in \mathbb{R}^m : u \geq 0, e^T u = 1\}$ , where  $e = (1, \dots, 1)^T \in \mathbb{R}^m$ , be a *vector of weights*. We consider only vectors of weights with zero weights for nonviolated constraints, i.e.,  $w_i = 0$  for  $i \in I \setminus I(\bar{x})$ .

If we multiply the particular inequalities of (1) by coordinates of a vector of weights  $w$  and we add formed inequalities then we obtain a *surrogate inequality (surrogate constraint)*

$$w^T G^T x \leq w^T b.$$

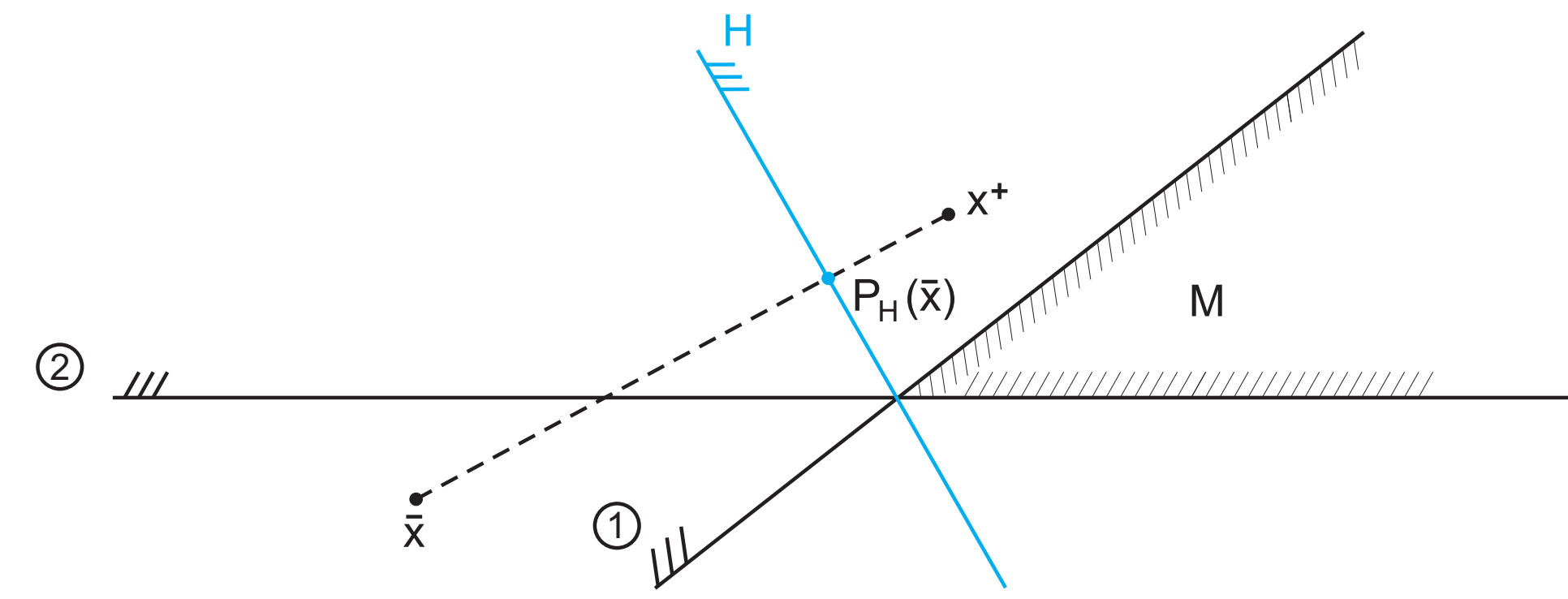
Of course  $M \subset H_w = \{x \in \mathbb{R}^n : w^T G^T x \leq w^T b\}$ . In one iteration of the *surrogate constraints method* we calculate a vector of weights  $w \in \Delta_m$  and a projection vector  $t(w)$  onto the halfspace  $H_w$ , i.e.,

$$t(w) = P_{H_w}(\bar{x}) - \bar{x}.$$

Thus, the next point  $x^+$  has the form

$$x^+ = \bar{x} + \lambda t(w), \quad (3)$$

where  $\lambda \in [0, 2]$  is a relaxation parameter.



## 2 Construction of a new surrogate constraint

Let  $\bar{x} \notin M$  be an approximation of a solution  $x^* \in M$  and let

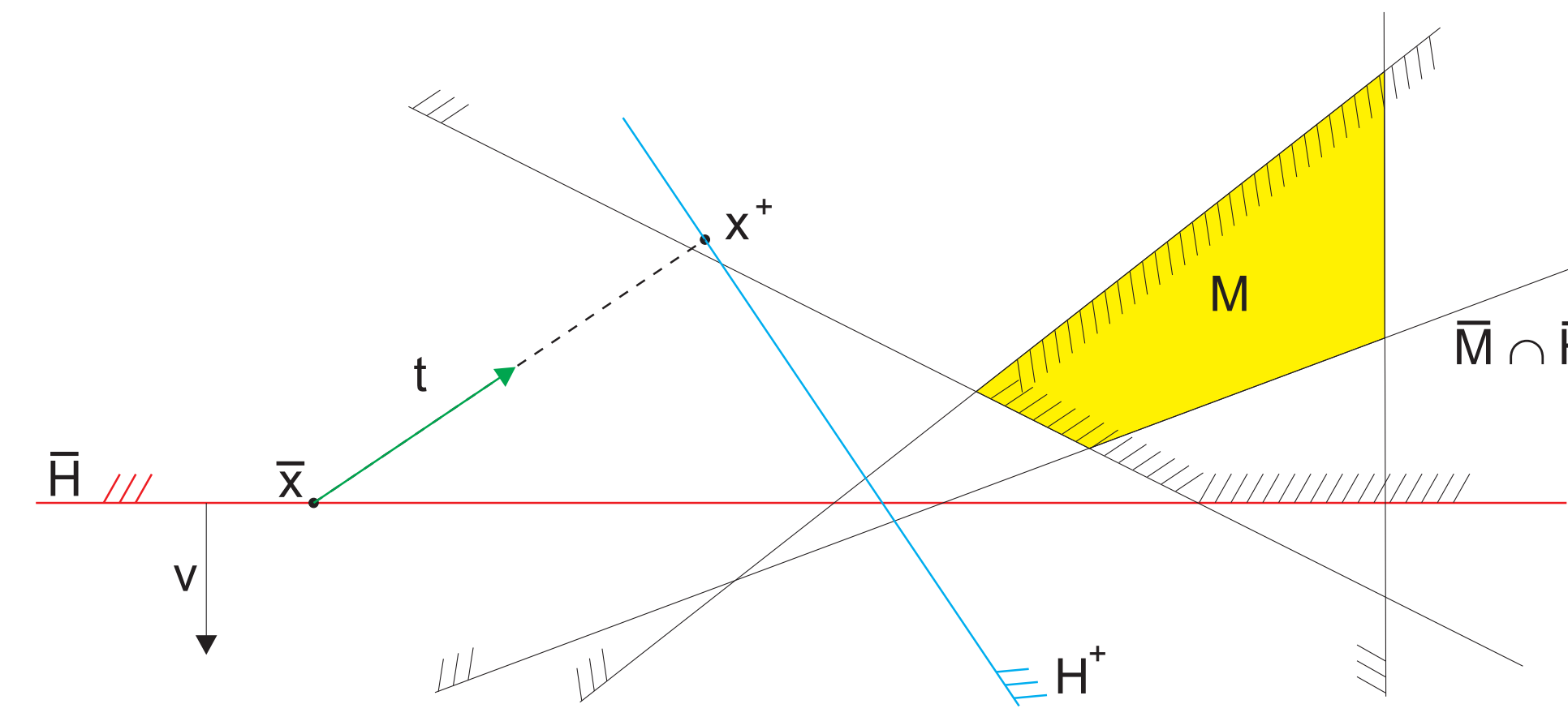
$$\bar{H} = H(\bar{x}) = \{x \in \mathbb{R}^n : v^T(x - \bar{x}) \leq 0\}$$

be a halfspace with a normal vector  $v \in \mathbb{R}$ , such that  $M \subset \bar{H}$ .

Make a new point  $x^+ \in \bar{H}$  which essentially better approximates a solution  $x^*$  will be our main aim. Let  $x^+$  has the form

$$x^+ = \bar{x} + \lambda t,$$

where  $\lambda \geq 0$  is a parameter and  $t \in \mathbb{R}^n$  is a direction of search.



We propose the following manner of evaluation of the vector  $t$ :

- evaluate a vector of weights  $w$ ,
- evaluate the vectors  $s^i$  for  $i \in I(\bar{x})$ , by (2),
- evaluate the projections  $P_{\bar{H}}(\bar{x} + s^i)$  for  $i \in I(\bar{x})$ ,
- set  $t = P_{\bar{H}}(\bar{x} + s^i) - \bar{x}$ .

In the point  $x^+$  we create a new surrogate inequality  $H^+$  with a normal vector  $-t$ . Thus,  $H^+$  has a following form

$$H^+ = \{x \in \mathbb{R}^n : -t^T(x - x^+) \leq 0\}.$$

In this Section we answer the question: how big may be the parameter  $\lambda$  to satisfy the condition  $M \subset H^+$ ?

Denote for  $i \in I(\bar{x})$

$$\hat{x}^i = \bar{x} + s^i, \quad (4)$$

$$y^i = P_{\bar{H}}(\hat{x}^i), \quad (5)$$

$$p^i = y^i - \hat{x}^i, \quad (6)$$

$$t^i = y^i - \bar{x}. \quad (7)$$

Let

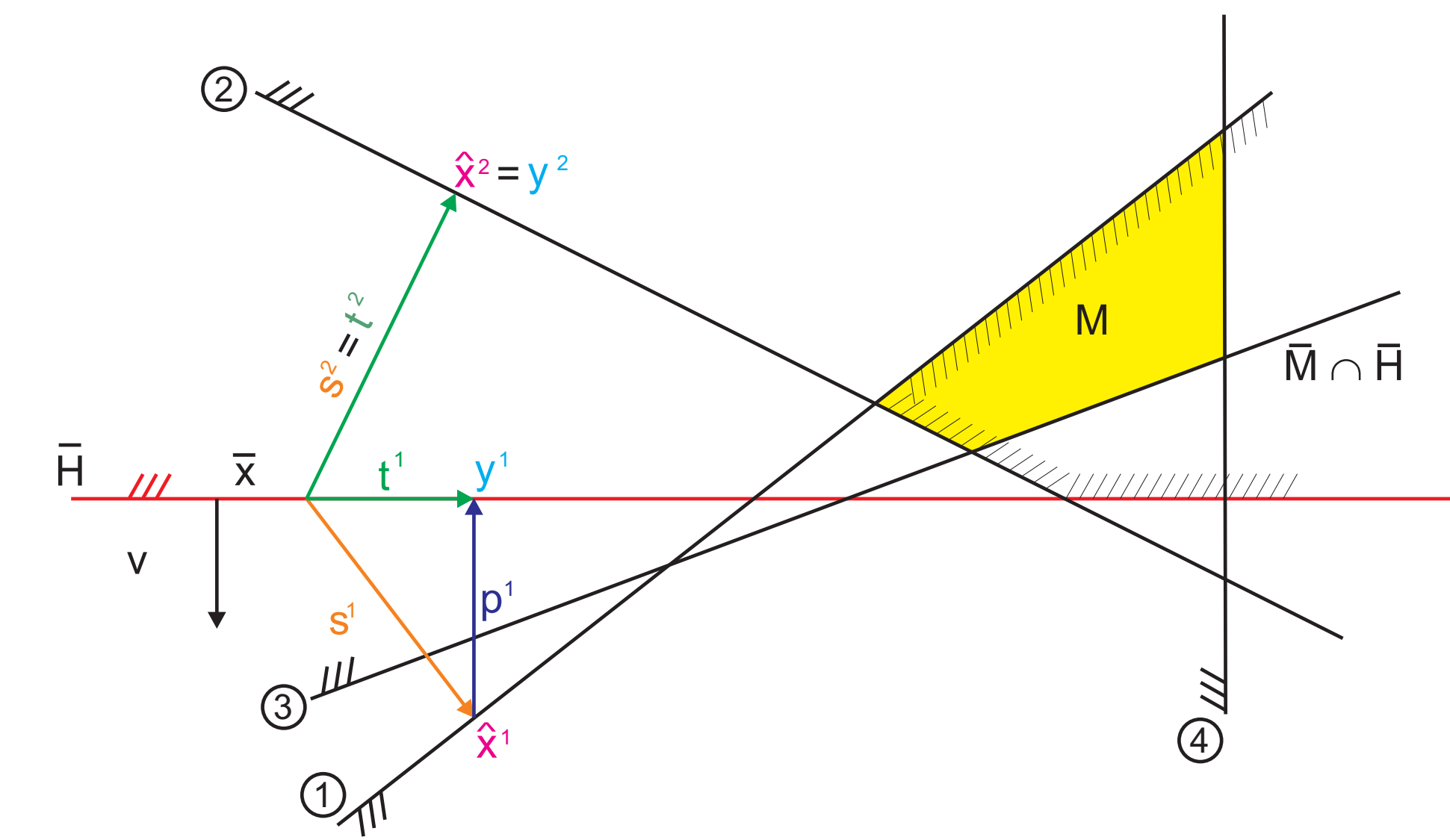
$$t = \sum_{i \in I(\bar{x})} w_i t^i$$

and

$$x^+ = \bar{x} + \lambda t,$$

where

$$\lambda = \mu \frac{\sum_{i \in I(\bar{x})} w_i \|s^i\|^2}{\left\| \sum_{i \in I(\bar{x})} w_i t^i \right\|^2}, \quad \mu \in (0, 2].$$



**Lemma 2.1** For each  $z \in \bar{M} \cap \bar{H}$  the following inequality is satisfied

$$\|x^+ - z\|^2 \leq \|\bar{x} - z\|^2 - \mu(2 - \mu) \frac{\left( \sum_{i \in I(\bar{x})} w_i \|s^i\|^2 \right)^2}{\left\| \sum_{i \in I(\bar{x})} w_i t^i \right\|^2}. \quad (8)$$

### 2.1 Iterative scheme

**Step 0. (Initialization)** Choose an arbitrary starting point  $x^{(0)}$ , an *optimality tolerance*  $\varepsilon > 0$ , a small positive quantity  $\gamma > 0$  and a quantity  $\delta \in (0, 1]$ . Set  $H^{(0)} = \mathbb{R}^n$  and  $k = 0$  (*iteration's counter*).

**Step 1. (Stopping criterion)** If  $x^{(k)}$  is an  $\varepsilon$ -optimal solution, i.e.,  $\max\{g_i^T x^{(k)} - b_i : i = 1, \dots, m\} \leq \varepsilon$ , terminate.

**Step 2. (Projection)** Evaluate for  $i \in I(x^{(k)})$

$$(a) s^{i(k)} = -(g_i^T x^{(k)} - b_i) g_i,$$

$$(b) \hat{x}^{i(k)} = x^{(k)} + s^{i(k)},$$

$$(c) y^{i(k)} = P_{H^k}(\hat{x}^{i(k)}),$$

$$(d) t^{i(k)} = y^{i(k)} - x^{(k)}.$$

**Step 3. (Approximation's update)**

$$(a) \text{ Evaluate } x^{(k+1)} = x^{(k)} + \mu \frac{\sum_{i \in I(x^{(k)})} w_i^{(k)} \|s^{i(k)}\|^2}{\left\| \sum_{i \in I(x^{(k)})} w_i^{(k)} t^{i(k)} \right\|^2} \cdot t^{(k)}, \text{ where}$$

$$t^{(k)} = \sum_{i \in I(x^{(k)})} w_i^{(k)} t^{i(k)} \text{ for a vector of weights } w^{(k)}, \text{ where } w_i^{(k)} > \gamma,$$

$$i \in I(x^{(k)}) \text{ and } \mu^{(k)} \in (\delta, 1],$$

$$(b) \text{ Set } v^{(k)} = x^{(k)} - x^{(k+1)},$$

$$(c) \text{ Set } H^{(k+1)} = \{x \in \mathbb{R}^n : v^{(k)T}(x - x^{(k+1)}) \leq 0\},$$

$$(d) \text{ Increase } k \text{ by 1 and go to Step 1.}$$

**Theorem 1** If  $M \neq \emptyset$ , then any infinite sequence  $(x^{(k)})_{k=0}^{\infty}$  generated by iterative scheme has the following properties:

(a)  $(x^{(k)})$  is strictly Fejér-monotone with respect to  $M$ ,

(b)  $\lim_{k \rightarrow \infty} \max_{i \in I(x^{(k)})} \|s^{i(k)}\| = 0$ .

Consequently,  $x^{(k)}$  converges to an  $x^* \in M$ .

## 3 Numerical results

The project can be summarized by the following scheme: We set  $\mu = 1$ ,  $\gamma = 10^{-3}$  and  $\varepsilon = 10^{-6}$ .

We have compared two methods: the surrogate constraints method of Yang-Murty [4] and the method presented in Section 2 (Iterative scheme).

For all presented methods we have performed the computation for two variants:

Variant I - equal weights for violated constraints, i.e.,  $w_i^{(k)} = \frac{1}{|I(x^{(k)})|}$ ,

Variant II - weights proportional to residuum of violated constraints

$$w_i^{(k)} = \max \left\{ \gamma, \frac{g_i^T x^{(k)} - b_i}{\sum_{i \in I(x^{(k)})} g_i^T x^{(k)} - b_i} \right\}, i \in I(x^{(k)}).$$

$n \times m$	$l$	Variant I		Variant II	
		Y-M	Iter. Schem. 2.1	Y-M	Iter. Schem. 2.1
20 × 20	12	23	9	25	14
	20	40	13	46	13
20 × 40	12	38	13	44	13
	24	71	18	76	19
20 × 80	12	55	15	65	17
	24	91	20	127	23
50 × 50	30	27	13	34	15
	50	38	16	53	18
50 × 100	30	49	18	62	20
	60	89	23	120	26
50 × 200	30	69	23	107	25
	60	178	32	235	34
100 × 100	60	29	14	40	17
	100	42	17	60	20
100 × 200	60	64	21	95	24
	120	116	28	171	30
200 × 200	120	30	16	43	18
	200	40	17	64	20
500 × 500	300	32	17	48	19
	500	36	18	55	20
500 × 1000	300	133	31	194	32
	500	234	40	348	52

## References

- [1] H. Scolnik, N. Echebest, M. T. Guardarucci, M. C. Vacchino, A class of optimized row projection methods for solving large nonsymmetric linear systems, *Applied Numerical Mathematics* **41** (2002) 499-513.
- [2] S. D. Flâm, J. Zowe, *Relaxed outer projections weighted averages and convex feasibility*, *BIT* **30** (1990) 289-300.
- [3] A. R. De Pierro, A. N. Iusem, *A simultaneous projection method for linear inequalities*, *Linear Algebra & Appl.* **64** (1985) 243-253.
- [4] K. Yang, K. G. Murty, *New Iterative Methods for Linear Inequalities*, *Journal of Optimization Theory and Applications* **72** (1992) 163-185.
- [5] L. G. Gurin, B. T. Polyak and E.V. Raik, *The method of projections for finding the common point of convex sets*, *USSR Comput. Math. and Math. Phys.* **7** (1967) 1-24.