EOUIVALENCE CLASSES IN THE OF EFFICIENT SOLUTIONS

with I = RP. If IO = RP

 $n \ll SO(t = \alpha)$, then there is

Sufficiency. Let use X having the Hold on Stone were the Tycyce of the LIANA LUPȘA, DOREL I. DUCA, EUGENIA DUCA (Cluj-Napoca) - (Aug.)

 $\sqrt{f}(x)$, if $x_{f,k}^0$, $f(x_{f,k}^0)$, $f(x_{f,k}^0)$, $f(x_{f,k}^0)$.

Let X be a nonvoid set of I^p , where by I we denote the set of integer numbers, let $f = (f_1, ..., f_p): X \to \mathbf{I}^p$ and let $s: X \to \mathbf{I}$, $s = f_1 + ... + f_p$

In the following, we denote by v-min (f; X) the vectorial optimization problem which possesses the constraint set X and the objective functions f_i , $j \in \{1, ..., p\}$.

DEFINITION 1. A point $x^0 \in X$ is said to be a min-efficient solution for v-min (f; X) if there is no $x \in X$ such that:

(1)
$$f_j(x) \le f_j(x^0)$$
 for each $j \in \{1, ..., p\}$

with at least one strict inequality.

 $u \in P(t = ct)$ and chRemark 1. Because $s(X) \subseteq I$, a point $x \in X$ is a min-efficient solution for problem v-min (f; X) if and only if there is no $y \in X$ such that

(2)
$$f_j(y) \le f_j(x), \text{ for each } j \in \{1, \dots, p\}$$

it is obvious that u \in SA(t = \alpha). Because X is a bounded set, it is also a finite

(3) The property of
$$s(y) \le s(x) - 1$$
. The property of $s(y) = s(y) = 1$.

Let min-EF(f; X) be the set of min-efficient solutions for problem v-min (f; X). In the set min-EF(f; X) we introduce the following equivalence relation: if x, y are in min-EF(f; X), we say that x is equivalent with y if

(4)
$$f(x) = f(y).$$

Since s(n) & L, s(V) & L, (8) is equivalent with If $t = (t_1, ..., t_p) \in \mathbb{R}^p$, then we agree that we denote by |t| the real number defined by $|t| = t_1 + \ldots + t_p$.

Let (P) be the following parametric programming problem:

(P)
$$\begin{cases} s(x) \to \min \\ f_j(x) \le t_j, \quad j \in \{1, \dots, p\} \\ x \in X \end{cases}$$

with $t \in \mathbb{R}^p$. If $t^0 \in \mathbb{R}^p$, then

i) by $P(t = t^0)$ we denote the problem LIANA LUPSA, DOREL I, DUCA, EUGENIA DUCA

$$\begin{cases} s(x) \to \min \left\{ - \frac{1}{p} \right\} \\ f_j(x) \le t_j^0, \quad j \in \{1, \dots, p\}, \\ x \in X \end{cases}$$
 and the particles and of each and find the biovening of X and X.

ii) by $SA(t=t^0)$ we denote the set of admissible solutions for $P(t=t^0)$,

(5)
$$SA(t = t^0) = \{x \in X: f_j(x) \le t_j^0, j \in \{1, ..., p\}\},$$

iii) by $SO(t = t^0)$ we denote the set of optimal solutions for $P(t = t^0)$. Let $T_0 = \{t^0 \in \mathbf{I}^p : SO(t=t^0) \neq \emptyset\}$.

THEOREM 1. If X is bounded, then a point $u \in X$ is a min-efficient solution for problem v-min (f, X) if and only if there is $\alpha \in T_0$ such that

(6)
$$u \in P(t = \alpha) \text{ and } s(u) = |\alpha|$$
.

Proof. Necessity. Let $u \in X$ be a min-efficient solution for problem v-min (f; X). Taking

(7)
$$\alpha = (f_1(u), \dots, f_p(u)) \in \mathbf{I}^p,$$

it is obvious that $u \in SA(t = \alpha)$. Because X is a bounded set, it is also a finite set. Then $SA(t = \alpha) \neq \emptyset$ implies that $SO(t = \alpha) \neq \emptyset$. Hence $\alpha \in T_0$. If $u \notin SO(t = \alpha)$, then there is $v \in X$ such that

for all
$$j \in \{1, ..., p\}$$
,

x, yours in min-EF (f. 22, we say that x is equivalent with y if

and

$$(8) s(v) < s(u).$$

Since $s(u) \in I$, $s(v) \in I$, (8) is equivalent with If $t = \{t_1, \dots, t_n\} \in \mathbb{R}^n$, then we agree that we denote by n the real number

$$s(v) \le s(u) - 1$$
.

In view of remark 1, u is not an efficient solution for v-min(f; X); that contradicts the assumption. Therefore u is an optimal solution for problem $P(t = \alpha)$ and, from (7), we get ii) $a_j \le a_j$ for each $j \in \{1, ..., p\}$ and there is $k \in \{1, ..., p\}$ such that

$$s(u) = f_1(u) + \ldots + f_p(u) = \alpha_1 + \ldots + \alpha_p = |\alpha|.$$

Then from (12), (14) and (15) we get that

Hence the condition is necessary. If $SA(t = \alpha) = \emptyset$, then the assertion (i) is true If $SA(t = \alpha) \neq \emptyset$ Then

Sufficiency. Let $u \in X$ having the property that there is $\beta \in T_0$ such that $u \in SO(t = \beta)$ and $s(u) = |\beta|$. If we suppose that u is not an efficient solution for v-min (f, X), then, in view of remark 1, there exists $v \in X$ such that

(9)
$$f_j(v) \le f_j(u), \ j \in \{1, ..., p\}$$

and

$$(10) \qquad \qquad > (^{0}x) \setminus \text{bas} (^{1}x)(v) \leq s(u) - 1. \quad (\forall) \quad \forall v \geq (^{0}x) \setminus (^{1}x)(v) = (^{1}x)(v) + (^{1}x)(v) = (^{1}x)(v) = (^{1}x)(v) + (^{1}x$$

But, because u is an optimal solution for $P(t = \beta)$, we have

Since $v \in X$, from (9) and (11) it results that $v \in SA(t = \beta)$. Then (10) implies $u \notin SO(t = \beta)$; that contradicts the assumption $u \in SO(t = \beta)$. Hence u is a min-efficient solution for problem v-min (f; X).

Because X is a finite set and $f(X) \subseteq \mathbf{I}^p$, there are $a = (a_1, ..., a_n) \in \mathbf{I}^p$ and $b = (b_1, ..., b_n) \in \mathbf{I}^p$ such that Obvious we have: a

(12)
$$a_j = \min\{f_j(x): x \in X\}, b_j = \max\{f_j(x): x \in X\}$$
 for all $j \in \{1, ..., p\}$.

Let
$$T = \underset{j=1}{\times} [a_j, b_j]$$
.

Let $T = \underset{j=1}{\times} [a_j, b_j]$.

We denote by $V(x) = 0$ and $v \in SA(x) = 0$.

LEMMA 2. If $\alpha \in \mathbf{I}^p \setminus T$, then one and only one of following assertions is true: $= \{(x)\}$

(i) $SA(t = \alpha) = \emptyset$;

(ii)
$$SO(t = \alpha) \neq \emptyset$$
, and for each $x^0 \in SO(t = \alpha)$ we have $s(x^0) \neq |\alpha|$.

Proof. We can be in one and only one of the two cases.

i) There is
$$k \in \{1, ..., p\}$$
 such that $\{1, ..., p\}$ such that

(13)
$$p_{cho}$$
 becomes $T_{ij}(r) = \text{tarty } \alpha_{ki} < a_{ki}$. (4) $=$ (5) R? \supseteq (5) $=$ 3) All swellor

Then by (12) we get that there is none $x \in X$ such that $f_k(x) \le \alpha_k$. Therefore $SA(t = \alpha) = \emptyset$.

ii) $a_j \le \alpha_j$ for each $j \in \{1, ..., p\}$, and there is $k \in \{1, ..., p\}$ such that

Hence the condition is necessary.

$$(14) b_k < \alpha_k.$$

130

If $SA(t = \alpha) = \emptyset$, then the assertion (i) is true. If $SA(t = \alpha) \neq \emptyset$, then, because X is a nonempty finite set, it follows that $SO(t = \alpha) \neq \emptyset$. Let $x^0 \in SO(t = \alpha)$. We have

(15)
$$f_j(x^0) \le \alpha_j, \ (\forall) \ j \in \{1, ..., p\}.$$

Then from (12), (14) and (15) we get that

$$f_j(x^0) \le \alpha_j, \ (\forall) \ j \in \{1, \dots, p\} \setminus \{k\} \text{ and } f_k(x^0) < \alpha_k.$$

That implies that $s(x^0) = \sum_{j=1}^{p} f_j(x^0) + f_k(x^0) < \sum_{j=1}^{p} \alpha_j = |\alpha|$. Hence $s(x^0) \neq |\alpha|$.

In the following, we join for each $\alpha \in T$ the set $V(\alpha)$ defined by

The contract is a finite set an element
$$V(\alpha) = V(\alpha)$$
 and $V(\alpha) = \sum_{j=1}^{p} [a_j, \alpha_j]$. The set $V(\alpha) = \sum_{j=1}^{p} [a_j, \alpha_j]$.

Obvious we have: I = I = m and that the I = (d, ..., d) = d but

LEMMA 3. If $\alpha \in T$, $\beta \in T$ and $\alpha \leq \beta$, then $SA(t = \alpha) \subseteq SA(t = \beta)$. This lemma has two important consequences.

COROLLARY 4. If $\beta \in T$ and $SA(t = \beta) = \emptyset$, then $SA(t = \alpha) = \emptyset$ for each $\alpha \in V(\beta)$.

Let $\beta \in T$ and $x \in SA(t = \beta)$. We denote by $U(f(x), \beta)$ the set

(17)
$$U(f(x),\beta) = \underset{j=1}{\times} [f_j(x),\beta_j].$$

COROLLARY 5. If $\beta \in T$ and $x^0 \in SO(t = \beta)$, then $x^0 \in SO(t = \alpha)$ for each $\alpha \in U(f(x^0), \beta)$.

Proof. Let $\alpha \in U(f(x^0), \beta)$. Then we get $\alpha \leq \beta$ and applying lemma 3 it follows $SA(t = \alpha) \subseteq SA(t = \beta)$. That implies that

(18) $\min\{f(x): x \in SA(t=\alpha)\} \ge \min\{f(x): x \in SA(t=\beta)\} = s(x^0).$

Because $\alpha \in U(f(x^0), \beta)$, we have

$$f_j(x^0) \le \alpha_j, \ (\forall) \ j \in \{1, \dots, p\}.$$

Henc

(19)
$$x^0 \in SA(t = \alpha).$$

From (18) and (19) it results that $x^0 \in SO(t = \alpha)$.

Let $\alpha \in T$. We denote

The matrix of the parameters
$$T_0(t=\alpha)=\sum\limits_{j=1}^p [\alpha_j,b_j]$$
 . If $x\in \mathbb{R}$, then to if

$$T_{1}(t = \alpha) = \begin{cases} [a_{1}, \alpha_{1}] \times \begin{pmatrix} p \\ \times [\alpha_{j}, b_{j}] \end{pmatrix}, a_{1} < \alpha_{1} \\ \emptyset, & a_{1} = \alpha_{1} \end{cases}$$

$$T_{p}(t = \alpha) = \begin{cases} p-1 & = \\ \times [a_{j}, b_{j}] \times [a_{p}, \alpha_{p}], \ a_{p} < \alpha_{p} \\ \varnothing, & a_{p} = \alpha_{p} \end{cases}$$

and, if p > 2,

$$T_i(t = \alpha) = \begin{cases} \sum_{j=1}^{i-1} [a_j, b_j] \times [a_i, \alpha_i] \times \begin{bmatrix} p \\ x \\ j=i+1 \end{bmatrix} [\alpha_j, b_j], \ a_i < \alpha_i, \\ \emptyset, \qquad a_i = \alpha_i \end{cases}$$

for $i \in \{2, ..., p-1\}$. = 134 × 140 = 14 (1) = (3 × 141) = 144 × 160 = 44

LEMMA 6. If $\alpha \in T$, then

(20)
$$T = \bigcup_{i=0}^{p} T_i.$$

Proof. Because $T_j(t = \alpha) \subseteq T$ for each $j \in \{0, 1, ..., p\}$, we get

$$(21) \qquad \qquad \bigcup_{i=0}^{p} T_i \subseteq T.$$

Let $t \in T$. Two cases are possible.

i) For each $j \in \{1, ..., p\}$ we have $t_j \ge \alpha_j$. Then $t_j \in [\alpha_j, b_j]$,

 $(\forall) \ j \in \{1, ..., p\}$. It follows that $t \in T_0(t = \alpha)$.

ii) There is $j \in \{1, ..., p\}$ such that $t_j < \alpha_j$. Let

(22)
$$k = \max\{j \in \{1, ..., p\}: t_j < \alpha_j\}.$$

We shall prove that $t \in T_k$.

For each $j \in \{1, ..., p\}$ we can be in one and only one of the three cases:

a) $j \in \{1, ..., k-1\}$ and then evidently $t_i \in [a_i, b_i]$;

b) j = k and then $t_k \in [a_j, \alpha_j]$;

c) $j \in \{k+1, ..., p\}$ and then, from (22) it follows that $t_j \ge \alpha_j$. Hence $t \in T_k(t=\alpha)$. Because t is arbitrary choosen in T, we get that

(23)
$$T \subseteq \bigcup_{i=0}^{p} T_i(t=\alpha).$$

From (21) and (23) it follows (20).

Using the conclusion of lemma 6 we give an algorithm for finding all equivalence classes for a vector optimization problem with integer variables.

DESCRIPTION OF THE ALGORITHM

Step 0. Put i: = 1, h: = 1, j: = 0, $T_1: = T$.

Step 1. For each $k \in \{1, ..., p\}$ put

 $u_k = \min\{t_k : t = (t_1, \dots, t_p) \in T_i\}, v_k = \max\{t_k : t = (t_1, \dots, t_p) \in T_i\}$

and take $t^{i} = (v_1, \dots, v_n)$.

Step 2. If $SA(t=t^i) = \emptyset$, then go to step 5.

If $SA(t=t^i) \neq \emptyset$, then choose $x^i \in SO(t=t^i)$ and put $\alpha = (f_1(x^i), \dots, f_p(x^i))$.

Step 3. Increase j with 1, put $y^j = x^i$ and k := 1.

Step 4. If $\alpha_k > u_k$, then put $T_{h+1} := T_k(t = \alpha)$, increase h with 1 and go to step 5. If $\alpha_k = u_k$, then go to step 5.

step 5. If $\alpha_k = u_k$, then go to step 5. Step 5. If k = p, then go to step 6. If $k \neq p$, then put k := k + 1 and return to step

Step 6. If i < h, then put i := i + 1 and return to step 1. If i = h, then the algorithm stops.

LEMMA 7. If X is a bounded set and j > 0, then the points y_r for $r \in \{1, ..., j\}$ are min-efficient solutions for problem v-min (f; X).

Proof. Let $r \in \{1, ..., j\}$. From step 3 we get that there exists $i \in \{1, ..., h\}$ such that $y^r = x^i$. But x^i is an optimal solution for problem $P(t = t^i)$. Then, in view of corollary 2, x^i is a min-efficient solution for problem v-min (f; X). It follows that y^r is also a min-efficient solution for problem v-min (f; X).

LEMMA 8. If X is a bounded set and j = 0, then the problem v-min (f, X) has not min-efficient solutions.

Proof. If $SA(t=t^1) \neq \emptyset$, then, because X is a finite set, the problem $P(t=t^1)$ has also optimal solutions. In view of steps 2 and 3 it follows that j > 0. Therefore it is not possible that we have $SA(t=t^1) \neq \emptyset$. If $SA(t=t^1) = \emptyset$, then, in view of step 2 we go to step 5. Because h=i=1, the algorithm is stopped. Hence, we have j=0 if and only if the problem $P(t=t^1)$ has not feasible solution, that is the system

(24)
$$\begin{cases} f_1(x) \le t_1^1 = b_1 \text{ and } f(X) \text{ for all } f(X) \\ \dots \text{ for a finite } f(X) \le t_p^1 = b_p \\ x \in X \end{cases}$$

is inconsistent. From (12) we get that if $x \in X$, then

$$f_k(x) \le b_k$$
, for each $k \in \{1, ..., p\}$.

That implies that the system (24) is inconsistent because $X = \emptyset$. Therefore, min- $EF(f; X) = \emptyset$.

THEOREM 9. If z is an efficient solution for v-min (f; X), then there is $i \in \{1, ..., h\}$ such that $z \in [x^i]$.

Proof. Because for each $i \in \{1, ..., h\}$ we have $t^i \in T_i \subseteq T$, we get that $SA(t = t^i) = \emptyset$ if and only if $X = \emptyset$. Hence, in the case $X \neq \emptyset$, the stop of the algorithm implies $\alpha = a$.

Let z be an efficient solution for v-min(f; X). In this case, in view of lemma 6, we get that $j \neq 0$. In view of theorem 1 there is $\beta \in T_0$ such that z is optimal solution for $P(t = \beta)$ and $s(z) = |\beta|$. From lemma 6 it results that there is $r \in \{1, ..., h\}$ such that

 $\beta \in TL_r$ and $\beta \notin TL_s$ for each $r \in \{1, ..., h\}$ with s > r. Let x^r be the optimal solution for the problem $P(t = t^r)$ taking in the step 2. From corollary 5, the set $U(f(x^r), t^r)$ has the property that x^r is also an optimal solution for problem $P(t=\tau)$ for all $\tau \in U(f(x^r), t^r)$. Because

$$T_r = U(T^r, x^r) \bigcup \left(\bigcup_{p=r+1}^h \{t \in T_p : t \in T_r\} \right)$$

and $\beta \notin T_s$ for each s > r, it follows that $\beta \in U(f(x^r), t^r)$.

Since z is an optimal solution for problem $P(t=\beta)$ and $s(z)=|\beta|$, we get that

(25)
$$f_j(z) = \beta_j, \text{ for each } j \in \{1, ..., p\}.$$

From $x^r \in SO(t = \tau)$ for some $\tau \in U(t^r, x^r)$, we have

(26)
$$f_j(z^r) \le \beta_j, j \in \{1, ..., p\}$$

it is not possible that we have $SA(t=t') = (S, H.SA(t=t') \mp (S_{cather,circuloss of$

and some with a part of the second standard and
$$s(x^r) = s(z) = |\beta|$$
. The large of the same second standard and the second second standard and the same second se

From (26) and (27) it results $= \frac{1}{2} (20)$

(28)
$$f_j(z) = f_j(x^r), \text{ for each } j \in \{1, ..., p\}.$$

Hence $z \in [x^r]$ *

THEOREM 10. If X is a bounded set, then the number of equivalence classes is finite.

Proof. If X is a bounded set, then $SZ = X \cap I^n$ is a finite set. Because for some efficient solutions x for v-min(f, X) we have $x \in X$, it is evident that the number of equivalence classes is finite.* min-EFYY: X) = O.

NUMERICAL EXAMPLE

 $u_i = \min\{i_i : i \in [t_i], i_i \in [t_i]\}$ To illustrate the algorithm we consider the following vectorial optimization problem: of the mark and the cases and mi sound to be X living both it is a fixed problem.

$$\begin{cases} v - \min f(x_1, x_2) = (-2x_1 + 3x_2^2, 3x_1^2 - 2x_2) \\ 0 \le x_1 \le 1 \end{cases}$$

$$0 \le x_2 \le 1$$

$$(x_1, x_2) \in \mathbf{I}^2$$

We have $T = [-2,3] \times [-2,3]$. The corresponding parametric programming problem is (2.1-) and (2.1-) and (2.1-) and (2.1-) and (2.1-) and (2.1-)

(30)
$$\begin{aligned}
\min s(x_1, x_2) &= 3x_1^2 + 3x_2^2 - 2x_1 - 2x_2 \\
&- 2x_1 + 3x_2^2 \le t_1 \\
&3x_1^2 - 2x_2 \le t_2 \\
&0 \le x_1 \le 1 \\
&0 \le x_2 \le 1 \\
&(x_1, x_2) \in \mathbf{I}^2
\end{aligned}$$

with $t \in T$, a Surin R.E., Multicolored decision making, Mathematical Programming $x, T \in T$ Step 0. Put i = 1, h = 1, j = 0, $T_1 = [-2,3] \times [-2,3]$.

Step 1. We have $u_1 = -2$, $u_2 = -2$, $v_1 = 3$, $v_3 = 3$. We take $t_1 = (3,3)$. Step 2. An optimal solution for the problem P(t = (3,3)) is $x^1 = (0,0)$. We take $\alpha = (0.0).$

Step 3. We take j = 1, $y^1 = (0,0)$ and k = 1.

Step 4. Because $\alpha_1 = 0 < -2 = u_1$, we put $T_2 = [-2,1] \times [0,3]$, increase h with 1 and go to step 5.001 beautiful to humanic distinct states and of the state of the s

Step 5. Because k = 1 < 2, increase k with 1 and return to step 4.

Step 4. Because $\alpha_2 = 0 > -2$, we put $T_3 = [-2, 3] \times [-2, -1]$, increase h with 1 and go to step 5.

Step 5. Since k=2, we go to step 6. And the standard was always

Step 6. Because $i \neq h$, we increase i with 1 and we go to step 1.

Step 1. We take $u_1 = -2$, $u_2 = 0$, $v_1 = -1$, $v_2 = 3$, and $t^2 = (-1,3)$.

Step 2. An optimal solution for the problem $P(t = t^2)$ is $x^2 = (1,0)$. We take $\alpha = (-2,3)$.

Step 3. We take j = 2, $y^2 = (1,0)$, k = 1.

Step 4. Because $\alpha_1 = -2 = u_1$, we go to step 5.

Step 5. Since k = 1 < 2, we take k = 2 and we go to step 4.

Step 4. Because $\alpha_2 = 3 > u_2$, we take $T_4 = [-2, -1] \times [0, 2]$, h = 4 and we go to step 5.

Step 5. Since k = 2, we go to step 6.

Step 6. Because i = 2 < 4 = h, we increase i with 1 and return to step 1.

Step 1. We take $u_1 = -2$, $u_2 = -2$, $v_1 = 3$, $v_2 = -1$ and $t_3 = (3, -1)$.

Step 2. $x^3 = (0,1)$ is an optimal solution for problem $P(t = t^3)$. We take $\alpha = (3, -2)$.

Step 3. We take j = 3, $y^3 = (0,1)$ and k = 1.

Step 4. Because $\alpha_1 > u_1$, we put $T_5 = [-2, 2] \times [-2, -1]$ and h = 5.

Step 5. We increase k with 1 and return to step 4.

Step 4. We increase k with 1.

Step 5. Because k = 2, we go to step 6.

Step 5. Since i = 3 < h = 5, we put i = 4 and we return to step 1.

Step 1. We take $u_1 = -2$, $u_2 = 0$, $v_1 = 2$, $v_2 = 2$ and $t_4 = (-1, 2)$.

Step 2. Because $SA(t = t^4) = \emptyset$, we go to step 6.

Step 5. Since i = 4 < h = 5, we increase i with 1 and we return to step 1.

Step 1. We take $u_1 = -2$, $u_2 = -2$, $v_1 = 2$, $v_2 = -1$ and $t^5 = (2, -1)$. Step 2. Since $SA(t = t^5) = \emptyset$, we go to step 5.

Step 5. Because i = 5 = h, the algorithm stops.

The equivalence classes of efficient solutions for vectorial problem (29) are: $[y^1] = [(0, 0)], [y^2] = [(1,0)], [y^3] = [(0,1)].$

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Sing 5. We increase & with I and which to stop 4