

b/ for  $k=1,2,\dots,n$  the functions  $\varphi_k$  are continuous and for fixed  $x_1, \dots, x_{k-1}, x_{k+1}, \dots, x_n$  they are concave in  $x_k$ . Under these assumptions the game has at least one equilibrium point.

Proof. See J.B. Rosen [8]. ■

Remark. If we assume that the functions  $\varphi_k$  are strictly concave in  $x_k$ , then the uniqueness of the equilibrium point in general is not true /see Example 4./. For the uniqueness of the equilibrium point of n-person games J.B. Rosen [8] gave sufficient conditions, but the assumptions of the next paragraphs are independent of the conditions introduced by J.B. Rosen.

## 2. The solution of a special class of concave games

Let us assume that for  $k=1,2,\dots,n$

$$X_k = \left\{ \underline{x}_k \mid \underline{x}_k \in R^{m_k}, \underline{h}_k(\underline{x}_k) \geq 0 \right\},$$

where

a/  $D(\underline{h}_k) = R^{m_k}$ ,  $\mathcal{R}(\underline{h}_k) \subset R^{l_k}$ , the components of  $\underline{h}_k$  are concave, continuously differentiable functions;

b/  $X_k$  is bounded, and in each point of  $X_k$  the Kuhn-Tucker regularity condition holds /see G. Hadley [3]/ ;

c/  $\varphi_k$  is continuous, concave in  $\underline{x}_k$  for fixed  $\underline{x}_1, \dots, \dots, \underline{x}_{k-1}, \underline{x}_{k+1}, \dots, \underline{x}_n$  and continuously differentiable with respect to  $\underline{x}_k$ .

Lemma 4. The game  $\Gamma = (n; X_1, \dots, X_n; \varphi_1, \dots, \varphi_n)$  has at least one equilibrium point.

Proof. It is obvious that all conditions of the Nikaido-Isoda theorem are satisfied. ■

Let  $k=1,2,\dots,n$  and for fixed strategy vector  $\underline{x}^{\#} = (x_1^{\#}, x_2^{\#}, \dots, x_n^{\#})$  consider the mathematical programming problem

$$\frac{h_k(\underline{x}_k) \geq 0}{\psi_k(\underline{x}_1^{\#}, \dots, \underline{x}_k, \dots, \underline{x}_n^{\#})} \rightarrow \max. \quad (8)$$

Lemma 5. A vector  $\underline{x}^{\#} = (x_1^{\#}, \dots, x_n^{\#})$  is an equilibrium point if and only if for  $k=1,2,\dots,n$   $\underline{x}_k^{\#}$  is an optimal solution of the problem (8).

Proof. a/ If  $\underline{x}_k^{\#}$  is a feasible solution, then the constraint implies that  $\underline{x}_k^{\#} \in X_k$ , thus  $\underline{x}^{\#} = (x_1^{\#}, \dots, x_n^{\#})$  is a strategy vector. If  $\underline{x}_k^{\#}$  is an optimal solution, then for any feasible solution  $\underline{x}_k \in X_k$ ,  $\psi_k(\underline{x}_1^{\#}, \dots, \underline{x}_k^{\#}, \dots, \underline{x}_n^{\#}) \geq \psi_k(\underline{x}_1^{\#}, \dots, \underline{x}_k, \dots, \underline{x}_n^{\#})$ . Thus  $\underline{x}^{\#}$  is an equilibrium point.

b/ If  $\underline{x}^{\#}$  is an equilibrium point, then inequalities (1) imply that the components  $\underline{x}_k^{\#}$  are optimal solutions of the problems (8). ■

Lemma 6. A vector  $\underline{x}^{\#} = (x_1^{\#}, \dots, x_n^{\#})$  is an equilibrium point if and only if for  $k=1,2,\dots,n$  there exists a vector  $\underline{u}_k \in R^{l_k}$  such that

$$\begin{aligned} \underline{u}_k &\geq 0 \\ \nabla_k \psi_k(\underline{x}^{\#}) + \underline{u}_k^T \nabla_k h_k(\underline{x}_k^{\#}) &= 0^T \\ h_k(\underline{x}_k^{\#}) &\geq 0 \\ \underline{u}_k^T h_k(\underline{x}_k^{\#}) &= 0 \end{aligned} \quad (9)$$

/where  $\nabla_k \varphi_k$  is the gradient vector of  $\varphi_k$  with respect to  $\underline{x}_k$  and  $\nabla_k h_k$  is the Jacobian matrix of  $h_k$  /.

Proof. Under the assumptions given above, problem (8) is a concave programming problem. It is known that the Kuhn-Tucker equations and inequalities (9) are sufficient and necessary conditions for the optimality of a vector  $\underline{x}_k^{\#}$  ( $k=1,2,\dots,n$ ) /see Hadley [3] / . ■

To the sake of simple notations let

$$\Psi_k(\underline{x}, \underline{u}_k) = \nabla_k f_k(\underline{x}) + \underline{u}_k^T \nabla_k h_k(\underline{x}_k),$$

where  $\underline{x} = (\underline{x}_1, \dots, \underline{x}_n)$ .

Now we can prove our main theorem.

Theorem 2. A vector  $\underline{x}^{\#} = (\underline{x}_1^{\#}, \dots, \underline{x}_n^{\#})$  is an equilibrium point if and only if there exists a vector  $\underline{u}^{\#} = (\underline{u}_1^{\#}, \dots, \underline{u}_n^{\#})$  such that  $(\underline{x}^{\#}, \underline{u}^{\#})$  is an optimal solution of the mathematical programming problem

$$\left. \begin{array}{l} \underline{u}_k \geq \underline{0} \\ \Psi_k(\underline{x}, \underline{u}_k) = \underline{0}^T \\ \underline{h}_k(\underline{x}_k) \geq \underline{0} \end{array} \right\} \quad (k=1,2,\dots,n) \quad (10)$$

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$$\sum_{k=1}^n \underline{u}_k^T \underline{h}_k(\underline{x}_k) \longrightarrow \min.$$

Proof. a/ Let  $\underline{x}^{\#}$  be an equilibrium point /Lemma 4. implies that there exists at least one equilibrium point./ Then there exists a vector  $\underline{u}^{\#} = (\underline{u}_1^{\#}, \dots, \underline{u}_n^{\#})$  such that the equations and inequalities are satisfied for  $\underline{u}_k = \underline{u}_k^{\#}$ , thus the value of the objective function of the programming problem (10) is zero for  $\underline{u}_k = \underline{u}_k^{\#}$ ,  $\underline{x}_k = \underline{x}_k^{\#}$ . For arbitrary feasible solution  $(\underline{x}, \underline{u})$



of (10) the objective function value is nonnegative, thus  $(\underline{x}^{\#}, \underline{u}^{\#})$  is an optimal solution.

b/ Let  $(\underline{x}^{\#}, \underline{u}^{\#})$  be an optimal solution of (10). Since it is a feasible solution, each term of the objective function is nonnegative, consequently the value of the objective function is nonnegative. But for the equilibrium point of the game /which exists/ the objective function has zero value, therefore the optimality of  $(\underline{x}^{\#}, \underline{u}^{\#})$  implies that the objective function at the point  $(\underline{x}^{\#}, \underline{u}^{\#})$  must have zero value. Since all terms are nonnegative in the objective function, all terms are equal to zero. Thus the equations and inequalities (9) are valid for  $\underline{x} = \underline{x}^{\#}$ ,  $\underline{u} = \underline{u}^{\#}$ , consequently Lemma 6. implies that  $\underline{x}^{\#}$  is an equilibrium point. ■

Remark 1. Problem (10) is a mathematical programming problem which can be solved by numerical methods /e.g. cutting plane or gradient type algorithms, see G. Hadley [3]/.

Remark 2. In the special case of  $n=2$  and  $\psi_2 = -\psi_1$  problem (10) was discovered by M.D. Canon [2].

Finally we will show well-known algorithms can be derived from the above general method as special cases.

### General polyhedral games

Using the notations of Example 3. we have

$$\begin{aligned}\nabla_k \psi_k(\underline{x}^{\#}) &= \underline{a}_k(\underline{x})^T \\ \nabla_k h_k(\underline{x}_k) &= -\underline{a}_k,\end{aligned}$$

since

$$\begin{aligned}\varphi_k(\underline{x}) &= \underline{a}_k(\underline{x})^T \underline{x}_k \\ \underline{h}_k(\underline{x}_k) &= \underline{b}_k - \underline{A}_k \underline{x}_k.\end{aligned}$$

Thus problem (10) has the form:

$$\left. \begin{aligned} \underline{u}_k &\geq \underline{0} \\ \underline{a}_k(\underline{x})^T - \underline{u}_k^T \underline{A}_k &= \underline{0}^T \\ \underline{b}_k - \underline{A}_k \underline{x}_k &\geq \underline{0} \end{aligned} \right\} \quad (k=1, 2, \dots, n) \quad (11)$$

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$$\sum_{k=1}^n \underline{u}_k^T (\underline{b}_k - \underline{A}_k \underline{x}_k) \longrightarrow \min.$$

Let us observe that the second constraint implies that

$$\underline{a}_k(\underline{x})^T = \underline{u}_k^T \underline{A}_k,$$

and by using the fact that  $\varphi_k(\underline{x}) = \underline{a}_k(\underline{x})^T \underline{x}_k$  we can write problem (11) in a more convenient form:

$$\left. \begin{aligned} \underline{u}_k &\geq \underline{0} \\ \underline{a}_k(\underline{x})^T - \underline{u}_k^T \underline{A}_k &= \underline{0}^T \\ \underline{b}_k - \underline{A}_k \underline{x}_k &\geq \underline{0} \end{aligned} \right\} \quad (k=1, 2, \dots, n)$$

---


$$\sum_{k=1}^n (\underline{u}_k^T \underline{b}_k - \varphi_k(\underline{x})) \longrightarrow \min. \quad (12)$$

As a special case let  $n=2$ . Since

$$\underline{a}_1(\underline{x}) = \underline{A} \underline{x}_2, \quad \underline{a}_2(\underline{x}) = \underline{B}^T \underline{x}_1,$$

where  $\underline{A} = \begin{pmatrix} a_{i_1 i_2}^{(1)} \end{pmatrix}$  and  $\underline{B} = \begin{pmatrix} a_{i_1 i_2}^{(2)} \end{pmatrix}$ ,

problem (12) can be rewritten as

$$\begin{aligned}
 \underline{u}_1 &\geq \underline{0} \\
 \underline{u}_2 &\geq \underline{0} \\
 \underline{x}_2^T \underline{A} - \underline{u}_1^T \underline{A}_1 &= \underline{0}^m \\
 \underline{x}_1^T \underline{B} - \underline{u}_2^T \underline{A}_2 &= \underline{0}^m \\
 \underline{b}_1 - \underline{A}_1 \underline{x}_1 &\geq \underline{0} \\
 \underline{b}_2 - \underline{A}_2 \underline{x}_2 &\geq \underline{0}
 \end{aligned} \tag{13}$$

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$$\sum_{k=1}^2 (\underline{u}_k^T \underline{b}_k) - \underline{x}_1^T (\underline{A} + \underline{B}) \underline{x}_2 \rightarrow \min ,$$

which is a quadratic programming problem with linear constraints. Let us observe that the unknown vector  $(\underline{x}_1, \underline{x}_2, \underline{u}_1, \underline{u}_2)$  is  $m_1 + m_2 + \ell_1 + \ell_2$  dimensional. In a further special case when  $\underline{B} = -\underline{A}$  /zero-sum case/, problem (13) is a linear programming problem, which can be solved by the simplex method.

### Mixed extension of finite games

As we have seen in Example 3, in our case

$$\underline{A}_k = \begin{pmatrix} -\underline{I} \\ \underline{1}^T \\ -\underline{1}^T \end{pmatrix}, \quad \underline{b}_k = \begin{pmatrix} \underline{0} \\ 1 \\ -1 \end{pmatrix}.$$

Let us write the vectors  $\underline{u}_k$  in block form corresponding to the special block form of  $\underline{A}_k$  and  $\underline{b}_k$ , then we have

$$\underline{u}_k = \begin{pmatrix} v_k \\ \alpha_k \\ \beta_k \end{pmatrix},$$

where  $\underline{v}_k \in R^{m_k}$ ,  $\alpha_k$  and  $\beta_k$  are scalars. Using these special notations problem (12) can be written in the form

$$\left. \begin{array}{l}
 \underline{v}_k \geq \underline{0} \\
 \alpha_k \geq 0 \\
 \beta_k \geq 0 \\
 \underline{a}_k (\underline{x})^T + \underline{v}_k^T - \alpha_k \underline{1}^T + \beta_k \underline{1}^T = \underline{0}^T \\
 \underline{x}_k \geq \underline{0} \\
 \underline{1}^T \underline{x}_k = 1
 \end{array} \right\} (k=1,2,\dots,n) \quad (14)$$


---


$$\sum_{k=1}^n \left( \alpha_k - \beta_k - \varphi_k(\underline{x}) \right) \rightarrow \min.$$

Let us observe that the nonnegative vector  $\underline{v}_k$  appears only in the fourth constraint and we can introduce the new variable  $\gamma_k = \alpha_k - \beta_k$ , which is not necessarily nonnegative. Then we get by multiplying the objective function by -1 the following problem:

$$\left. \begin{array}{l}
 \underline{a}_k (\underline{x})^T \leq \gamma_k \underline{1}^T \\
 \underline{x}_k \geq \underline{0} \\
 \underline{1}^T \underline{x}_k = 1
 \end{array} \right\} (k=1,2,\dots,n) \quad (15)$$


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$$\sum_{k=1}^n \left( \varphi_k(\underline{x}) - \gamma_k \right) \rightarrow \max$$

which is the method of H. Mills [6].

### Bimatrix games

From the previous case the bimatrix games can be obtained by choosing  $n=2$ . Simple calculations show that

$$\underline{a}_1(\underline{x}) = \underline{A} \underline{x}_2, \quad \underline{a}_2(\underline{x}) = \underline{B}^T \underline{x}_1,$$

thus problem (15) can be written as

$$\begin{aligned} \underline{A} \underline{x}_2 &\leq \gamma_1 \underline{1} \\ \underline{B}^T \underline{x}_1 &\leq \gamma_2 \underline{1} \\ \underline{x}_1 &\geq \underline{0} \\ \underline{x}_2 &\geq \underline{0} \end{aligned} \tag{16}$$

$$\begin{aligned} \underline{1}^T \underline{x}_1 &= 1 \\ \underline{1}^T \underline{x}_2 &= 1 \end{aligned}$$

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$$\underline{x}_1^T (\underline{A} + \underline{B}) \underline{x}_2 - \gamma_1 - \gamma_2 \rightarrow \max,$$

which is a quadratic programming problem with linear constraints and it was discovered by O.L. Mangasarian and H. Stone [5].

For matrix games  $\underline{B} = -\underline{A}$ , thus problem (16) is a linear programming problem, which can be separated with respect to the variables  $(\underline{x}_1, \gamma_2)$  and  $(\underline{x}_2, \gamma_1)$ , and so problem (16) can be reduced for two linear programming problems

$$\begin{aligned} \underline{A} \underline{x}_2 &\leq \gamma_1 \underline{1} \\ \underline{x}_2 &\geq \underline{0} \\ \underline{1}^T \underline{x}_2 &= 1 \end{aligned} \tag{17}$$

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$$\gamma_1 \rightarrow \min$$

and

$$\begin{aligned} -\underline{A}^T \underline{x}_1 &\leq \gamma_2 \underline{1} \\ \underline{x}_1 &\geq \underline{0} \\ \underline{1}^T \underline{x}_1 &= 1 \end{aligned} \tag{18}$$

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$$\gamma_2 \rightarrow \min,$$

where the problems have  $m_2 + 1$  and  $m_1 + 1$  variables, respectively.