

$$\text{opt} \{ f(\bar{x}) \} / \bar{x} \in \mathcal{D} \subseteq \mathcal{R}^n$$

nelineární funkce nebo podmínky.

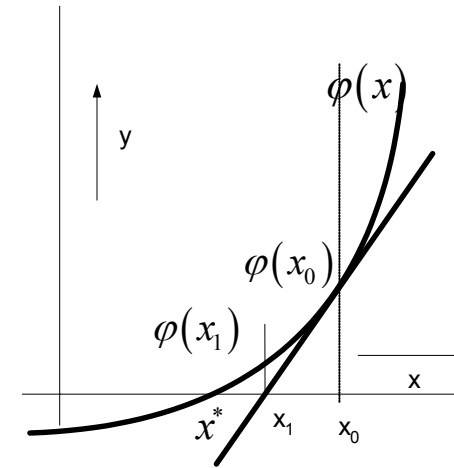
**Obecný algoritmus optimalizace:**

1. iniciace startovacího bodu  $\bar{\xi}^0$  ;  $k=1$
2. stanovení směru pohybu  $D^{(k)}$
3. určení optimálního kroku  $\alpha^{(k)}$
4. aktualizace  $\bar{\xi}^{k+1} = \bar{\xi}^k + \alpha^k \cdot \bar{D}^k$
5. je li optimalita true pak konec  
jinak  $k:=k+1$  a návrat na bod 2)

**Metody:**

1	Newton	9 (NR, Quasi-Newton)
2	Spádové metody	(maximální spád, konjugovaný gradient, DFP,BFG, redukovaný gradient)
3	Vnitřní trajektorie	

## Newtonovský přístup



$$\varphi(x_0) + \frac{\partial \varphi(x)_0}{\partial x} \underbrace{(x_1 - x_0)}_{\Delta x} = 0$$

$$\Delta x = - \frac{\partial \varphi(x)_0}{\partial x}^{-1} \varphi(x_0)$$

$$x_1 = x_0 + \Delta x$$

$$\bar{x} = [x_1, \dots, x_{\partial x}]^T$$

$$\bar{y} = [\varphi_1, \dots, \varphi_{\partial y}]^T$$

$$[J] = \begin{bmatrix} \left[ \frac{\partial \varphi_1}{\partial x_1}, \dots, \frac{\partial \varphi_1}{\partial x_{\partial x}} \right] \\ \dots \\ \left[ \frac{\partial \varphi_{\partial y}}{\partial x_1}, \dots, \frac{\partial \varphi_{\partial y}}{\partial x_{\partial x}} \right] \end{bmatrix}$$

$$\bar{\varphi}(\bar{x}_0) + [J_0] \Delta \bar{x} = \bar{0} \Rightarrow \Delta \bar{x} = -[J_0]^{-1} \bar{\varphi}(\bar{x}_0),$$

$$\bar{x}_1 = \bar{x}_0 + \Delta \bar{x}$$

**Podmínky pro nulování:**

BPF	Zadané bilance uzlů
OPF	Gradient Lagrangiánu

## Postupné kvadratické programování:

$$H(\bar{\xi}^{(k)}) \cdot \bar{D}^{(k)} = -\nabla f(\bar{\xi}^{(k)})$$

### Základní algoritmus Newtonova přístupu:

1. iniciace.  $k=0$ ,  $\bar{\xi} = \bar{\xi}^0$
2. výpočet  $\nabla L^{(k)}$ ,  
stanovení množiny aktivních omezení
3. je li optimalita true pak konec  
jinak pokračuj
4. stanovení  $[J^{(k)}]$ ,  $[H^{(k)}]$ ,  $[W^{(k)}]$
5. řešení rovnice  $[W^{(k)}] \cdot \Delta \bar{\xi}^{(k)} = -\nabla \bar{L}^{(k)}$  ;  
event. obsluha omezení
6. korekce  $\bar{\xi}^{(k+1)} = \bar{\xi}^{(k)} + \Delta \bar{\xi}^{(k)}$   
 $k=k+1$ , návrat na 2.

## Metoda největšího spádu .

$F(\bar{v})$ ,  $\bar{v} = [v_1, \dots, v_{\partial v}]^T$ , ...funkce, vektor proměnných

$\nabla^T F(\bar{v}) = [g_1, \dots, g_{\partial v}]^T = \bar{g}(\bar{v})$ .....gradient funkce

$\bar{D} = [d_1, \dots, d_{\partial v}]^T$ , ...normovaný směrový vektor  $\left( \sum_{v_i} d_i^2 = 1 \right)$

Derivace ve směru  $\bar{D}$

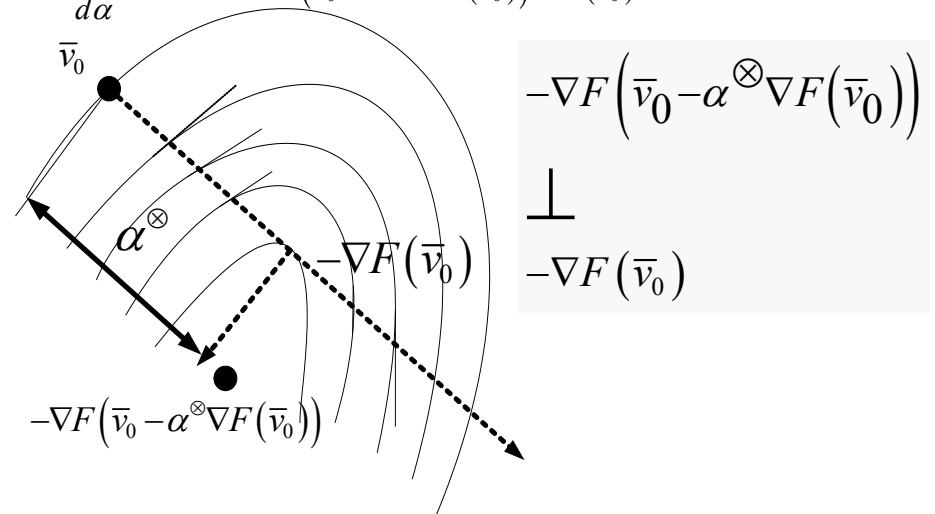
$v_i = v_{0i} + t \cdot d_i \Rightarrow dv_i / dt = d_i$

$$\frac{dF(\bar{v}_0)}{d\bar{D}} = \lim_{t \rightarrow 0} \frac{F(\bar{v}_0 + t \cdot \bar{D}) - F(\bar{v}_0)}{t} = \sum_{i=1}^{\partial v} \overbrace{\frac{\partial F(\bar{v})}{\partial v_i}}^{g_{i0}} \frac{d_i}{dt} = \nabla F(\bar{v}_0) \cdot \bar{D}$$

$\alpha$ ...vzdálenost od  $\bar{v}_0$ ,  $\bar{D} = -\nabla^T F(\bar{v}_0)$ ...směr gradientní metody

$F\left(\overbrace{\bar{v}_0 + \alpha \bar{D}}^{\bar{v}}\right) = \Phi(\alpha)$ ,  $\alpha^{\otimes} = \arg \min \Phi(\alpha)$ ..optimální krok

$\frac{d\Phi(\alpha)}{d\alpha} = 0; \Rightarrow \nabla^T F(\bar{v}_0 - \alpha^{\otimes} \nabla^T F(\bar{v}_0)) \cdot \nabla F(\bar{v}_0) = 0$  součin  $\perp$  směří



$$\bar{v}_{k+1} = \bar{v}_k - \alpha_k \bar{g}_k,$$

$$\alpha_k = \arg \min_{\alpha > 0} F(\bar{v}_k - \alpha \bar{g}_k) \Rightarrow \frac{\partial F(\bar{v}_k - \alpha \bar{g}_k)}{\partial \alpha} = 0$$

kvadratická aproximace:

$$F(\bar{v}) = F(\bar{v}^*) + \frac{1}{2}(\bar{v} - \bar{v}^*)^T [H](\bar{v} - \bar{v}^*)$$

$$\left( \frac{\partial F(\bar{v})}{\partial \bar{v}} \right)^T = [H](\bar{v} - \bar{v}^*) = \bar{g}(\bar{v})$$

$$\left( \frac{\partial^2 F(\bar{v})}{\partial \bar{v}^2} \right) = [H]$$

$$F(\bar{v}_{k+1}) = F(\bar{v}^*) + \frac{1}{2}(\bar{v}_k - \alpha_k \bar{g}_k - \bar{v}^*)^T [H](\bar{v}_k - \alpha_k \bar{g}_k - \bar{v}^*) = \Phi(\alpha_k)$$

$$\frac{\partial \Phi(\alpha_k)}{\partial \alpha_k} = \alpha_k \bar{g}_k^T [H] \bar{g}_k - \bar{g}_k^T [H](\bar{v}_k - \bar{v}^*) = 0$$

$$\alpha_k = \frac{\bar{g}_k^T [H](\bar{v}_k - \bar{v}^*)}{\bar{g}_k^T [H] \bar{g}_k} = \frac{\bar{g}_k^T \bar{g}_k}{\bar{g}_k^T [H] \bar{g}_k}$$

## Metoda konjugovaných směrů.

$$\bar{s}_i [Q] \bar{s}_j = 0 \quad \forall i, j, \quad i \neq j$$

$\bar{s}$ ....směry konjugované k  $[Q]$

$[Q]$ ...symetrická poz.def. matice

$$F(\bar{v}) = \bar{a}^T \bar{v} + \frac{1}{2} \bar{v}^T [Q] \bar{v}$$

$$\bar{g}_k(\bar{v}) = \bar{a} + [Q] \bar{v}, \Rightarrow 0 = \bar{a} + [Q] \bar{v}^*$$

předpoklad: známe  $\bar{s}_k, k = 0 \dots n-1$

$$\bar{v}_{k+1} = \bar{v}_k + \alpha_k \bar{s}_k, \quad \alpha_k = \arg \min_{\alpha > 0} F(\bar{v}_k + \alpha \bar{s}_k)$$

$$\bar{v}_k - \bar{v}_0 = \sum_{j=0}^{k-1} \alpha_j \bar{s}_j$$

$$\bar{s}_k^T [Q](\bar{v}_k - \bar{v}_0) = 0 \Rightarrow \bar{s}_k^T [Q] \bar{v}_k = \bar{s}_k^T [Q] \bar{v}_0$$

$$\bar{v}_n - \bar{v}_0 = \sum_{j=0}^{n-1} \alpha_j \bar{s}_j$$

$$\bar{s}_k^T [Q](\bar{v}_n - \bar{v}_0) = \sum_{j=0}^{n-1} \alpha_j \bar{s}_j^T [Q] \bar{s}_k = \alpha_k \bar{s}_k^T [Q] \bar{s}_k$$

$$\alpha_k = \frac{\bar{s}_k^T [Q](\bar{v}_n - \bar{v}_0)}{\bar{s}_k^T [Q] \bar{s}_k} = \frac{\bar{s}_k^T \left( \underbrace{-\bar{a}}_{[Q] \bar{v}^*} - \underbrace{\bar{g}_k}_{[Q] \bar{v}_k} \right)}{\bar{s}_k^T [Q] \bar{s}_k} = - \frac{\bar{s}_k^T \bar{g}_k}{\bar{s}_k^T [Q] \bar{s}_k}$$

# Redukovaný gradient $\nabla_{\bar{\rho}} F$

$$\text{cílová funkce: } F\left(\underbrace{\bar{\rho}, \bar{\sigma}(\bar{\rho})}_{\bar{x}}\right), \quad \bar{\rho}, (\bar{\sigma} = \bar{\sigma}(\bar{\rho}))$$

vektor nezávisle,  
(závisle) proměnných

$$\bar{x} = \begin{bmatrix} \bar{\rho} \\ \bar{\sigma} \end{bmatrix} \dots \dots \bar{\sigma} - \text{rozm. složený vektor proměnných}$$

$$\bar{\mathcal{R}}(\bar{\rho}, \bar{\sigma}) = \bar{\partial \mathcal{R}} - \text{rozm. vektor vazeb.podmínek:}$$

$$0 = d\bar{\mathcal{R}}(\bar{\rho}, \bar{\sigma}) = \left(\frac{\partial \bar{\mathcal{R}}}{\partial \bar{\rho}}\right) d\bar{\rho} + \left(\frac{\partial \bar{\mathcal{R}}}{\partial \bar{\sigma}}\right) d\bar{\sigma} \Rightarrow$$

$$\Rightarrow \frac{d\bar{\mathcal{R}}(\bar{\rho}, \bar{\sigma})}{d\bar{\rho}} = \left(\frac{\partial \bar{\mathcal{R}}}{\partial \bar{\rho}}\right) + \left(\frac{\partial \bar{\mathcal{R}}}{\partial \bar{\sigma}}\right) \cdot \left(\frac{d\bar{\sigma}}{d\bar{\rho}}\right) \Rightarrow$$

$$\Rightarrow \frac{d\bar{\sigma}}{d\bar{\rho}} = - \left[ \frac{\partial \bar{\mathcal{R}}}{\partial \bar{\sigma}} \right]^{-1} \cdot \frac{\partial \bar{\mathcal{R}}}{\partial \bar{\rho}} = \begin{bmatrix} \frac{d\sigma_1}{\partial \rho_1} & \frac{\partial \sigma_1}{\partial \rho_{\partial x}} \\ \cdot & \cdot \\ \frac{\partial \sigma_{\partial \mathcal{R}}}{\partial \rho_1} & \frac{\partial \sigma_{\partial \mathcal{R}}}{\partial \rho_{\partial x}} \end{bmatrix}$$

$$\nabla_{F_{\rho}} = \frac{dF}{d\bar{\rho}} = \begin{bmatrix} \frac{dF}{d\rho_1} \\ \cdot \\ \frac{dF}{d\rho_{\partial x}} \end{bmatrix} = \begin{bmatrix} \frac{\partial F}{\partial \rho_1} + \sum_{j=1}^M \frac{\partial F}{\partial \sigma_j} \cdot \frac{\partial \sigma_j}{\partial \rho_1} \\ \cdot \\ \frac{\partial F}{\partial \rho_{\partial x}} + \sum_{j=1}^M \frac{\partial F}{\partial \sigma_j} \cdot \frac{\partial \sigma_j}{\partial \rho_{\partial x}} \end{bmatrix}$$

$$\frac{dF}{d\bar{\rho}} = \nabla_{F_{\rho}} + \left[ \frac{\partial \bar{\sigma}}{\partial \bar{\rho}} \right]^T \nabla_{F_{\sigma}} = \nabla_{F_{\rho}} + \left( \nabla_{F_{\sigma}}^T \left[ \frac{\partial \bar{\sigma}}{\partial \bar{\rho}} \right] \right)^T$$

$$\frac{dF}{d\bar{\rho}} = \nabla_{F_{\rho}} - \left( \nabla_{F_{\sigma}}^T \cdot \left[ \frac{\partial \bar{\mathcal{R}}}{\partial \bar{\sigma}} \right]^{-1} \cdot \frac{\partial \bar{\mathcal{R}}}{\partial \bar{\rho}} \right)^T$$

## formulace optimálního režimu:

$$L(\bar{x}) = F(\bar{x}) + \bar{\lambda}_R^T \cdot \underbrace{\bar{\mathcal{R}}(\bar{x})}_{\text{podmínky chodu}} + \underbrace{\Psi_p(\bar{x})}_{\text{penalizace}}$$

## podmínky 1.řádu:

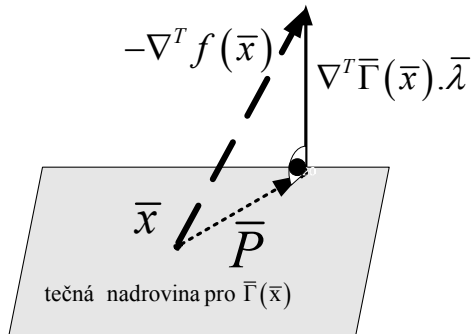
$$\frac{\partial L}{\partial \bar{\sigma}} = \frac{\partial F}{\partial \bar{\sigma}} + \frac{\partial \bar{\mathcal{R}}(\bar{x})}{\partial \bar{\sigma}} \cdot \bar{\lambda} = 0 \Rightarrow \bar{\lambda} = - \left[ \frac{\partial \bar{\mathcal{R}}^T}{\partial \bar{\sigma}} \right] \left( \frac{\partial F}{\partial \bar{\sigma}} \right),$$

$$\frac{\partial L}{\partial \bar{\rho}} = \frac{\partial F}{\partial \bar{\rho}} + \frac{\partial \bar{\mathcal{R}}(\bar{x})}{\partial \bar{\rho}} \cdot \bar{\lambda} = 0, \quad \frac{\partial L}{\partial \bar{\lambda}} = \bar{\mathcal{R}}(\bar{x}) = 0$$

$$\nabla_{\rho} L = \frac{\partial F}{\partial \bar{\rho}} - \frac{\partial \bar{\mathcal{R}}(\bar{x})}{\partial \bar{\rho}} \cdot \underbrace{\left[ \frac{\partial \bar{\mathcal{R}}^T}{\partial \bar{\sigma}} \right] \left( \frac{\partial F}{\partial \bar{\sigma}} \right)}_{-\bar{\lambda}}$$

**Projektovaný gradient.**

$$L = F(\bar{x}) + \bar{\lambda}^T \cdot \bar{\Gamma}(\bar{x}) \quad \dots \text{Lagrangeova funkce}$$



*KKT podmínky pro  $\nabla^T F(\bar{x}^*) \uparrow \nabla^T \bar{\Gamma}(\bar{x}^*)$*

$$\nabla^T F(\bar{x}^*) + [\nabla^T \bar{\Gamma}(\bar{x}^*)] \cdot \bar{\lambda} = \bar{0} \quad \text{v optimu}$$

$\bar{P} = -\nabla^T F - [\nabla^T \bar{\Gamma}] \cdot \bar{\lambda}$  ..hledaný směr projekce gradientu

$$[\nabla \bar{\Gamma}] \cdot \bar{P} = 0, \quad [\nabla^T \bar{\Gamma}] \bar{\lambda} \text{ a } \bar{P} \text{ jsou navzájem kolmé}$$

$$0 = -[\nabla \bar{\Gamma}] \nabla^T F - [\nabla \bar{\Gamma}] \cdot [\nabla^T \bar{\Gamma}] \cdot \bar{\lambda} \Rightarrow$$

$$\bar{\lambda} = -(\nabla \bar{\Gamma} \cdot \nabla^T \bar{\Gamma})^{-1} \nabla \bar{\Gamma} \cdot \nabla^T F$$

$$\bar{P} = - \underbrace{\left\{ [\text{diag } \mathbf{1}] - \nabla^T \bar{\Gamma} \cdot (\nabla \bar{\Gamma} \cdot \nabla^T \bar{\Gamma})^{-1} \nabla \bar{\Gamma} \right\}}_{\text{Projekční matice}} \cdot \nabla^T F$$

**Spádové metody**

**(redukovaný gradient):**

$$\bar{D}^{(k)} = -\nabla^T L(\bar{\xi}^{(k)})$$

**Výpočetní postup:**

<b>1</b>	$\bar{\rho} = \bar{\rho}_0, \quad \mathbf{k}=1$	<b>Počáteční iniciace</b>
<b>2</b>	$\bar{\mathcal{R}}(\bar{x}) = \bar{0}$	<b>Řešení ustáleného stavu</b>
<b>3</b>	$\bar{\lambda} = - \left[ \frac{\partial \bar{\mathcal{R}}^T}{\partial \bar{\sigma}} \right] \left( \frac{\partial F}{\partial \bar{\sigma}} \right)$	<b>Výpočet <math>\bar{\lambda}</math></b>
<b>4</b>	$\nabla_{\bar{\rho}} F = \frac{\partial F}{\partial \bar{\rho}} + \frac{\partial \bar{\mathcal{R}}(\bar{x})}{\partial \bar{\rho}} \cdot \bar{\lambda}$	<b>Výpočet <math>\nabla_{\bar{\rho}} F</math></b>
<b>5</b>	$\nabla'_{\bar{\rho}} F$	<b>projekce <math>\nabla_{\bar{\rho}} F</math></b>
<b>6</b>	<i>if <math> \nabla'_u F  \leq \varepsilon</math> pak END else 7</i>	<b>kontrola optimality</b>
<b>7</b>	$\alpha = \text{opt}(\bullet)$	<b>Určení kroku <math>\alpha</math></b>
<b>8</b>	$\bar{\rho} = \bar{\rho} - \alpha \cdot \nabla_{\bar{\rho}} F'_u$	<b>korekce</b>
<b>9</b>	$\mathbf{k}=\mathbf{k}+1; \quad \text{Goto 2}$	<b>návrat</b>