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Anexo 1

Funções para Medida de Desempenho

Função Sphere Deslocada

$$f_1(\mathbf{x}) = \sum_{i=1}^{D} z_i^2 + bias_1$$

$$\mathbf{z} = \mathbf{x} - \mathbf{o}, \mathbf{x} = [x_1, x_2, \cdots, x_D]$$

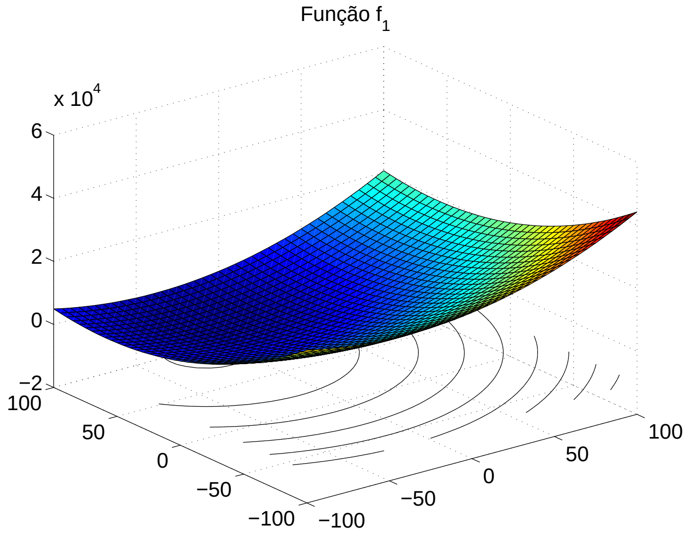

Figura 5.3: Mapa 3D da função f_1.

- Unimodal
- Deslocamento da origem
- Separável
- Escalonável
- $\mathbf{x} \in [-100, 100]^D$, Ótimo global: $\mathbf{x}^* = \mathbf{o}$, $F_1(\mathbf{x}^*) = bias_1 = -450$

Função Schwefel Deslocada

$$f_2(\mathbf{x}) = \sum_{i=1}^{D} \left(\sum_{j=1}^{i} z_j \right)^2 + bias_2$$

$$\mathbf{z} = \mathbf{x} - \mathbf{o}, \mathbf{x} = [x_1, x_2, \cdots, x_D]$$

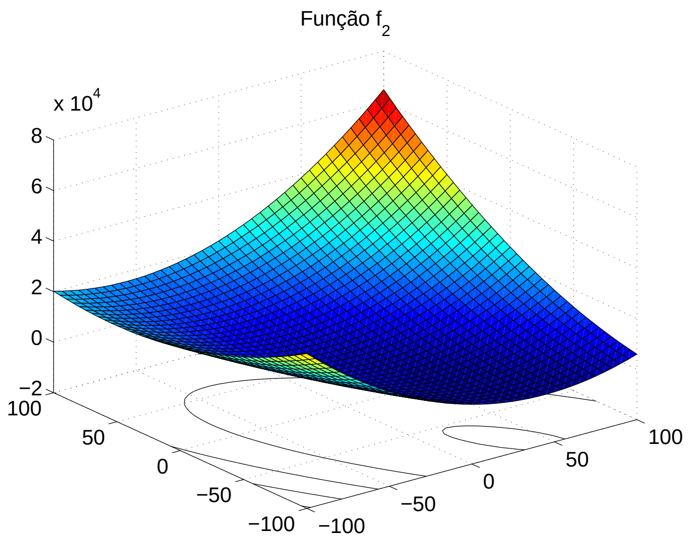

Figura 5.4: Mapa 3D da função f_2.

- Unimodal
- Deslocamento da origem
- Não-separável
- Escalonável
- $\mathbf{x} \in [-100, 100]^D$, Ótimo global: $\mathbf{x}^* = \mathbf{o}$, $F_2(\mathbf{x}^*) = bias_2 = -450$

Função Elíptica Rotacionada e Deslocada

$$f_3(\mathbf{x}) = \sum_{i=1}^{D} \left(10^6\right)^{\frac{i-1}{D-1}} z_i^2 + bias_3$$

$$\mathbf{z} = (\mathbf{x} - \mathbf{o}) \cdot \mathbf{M}, \mathbf{x} = [x_1, x_2, \cdots, x_D]$$

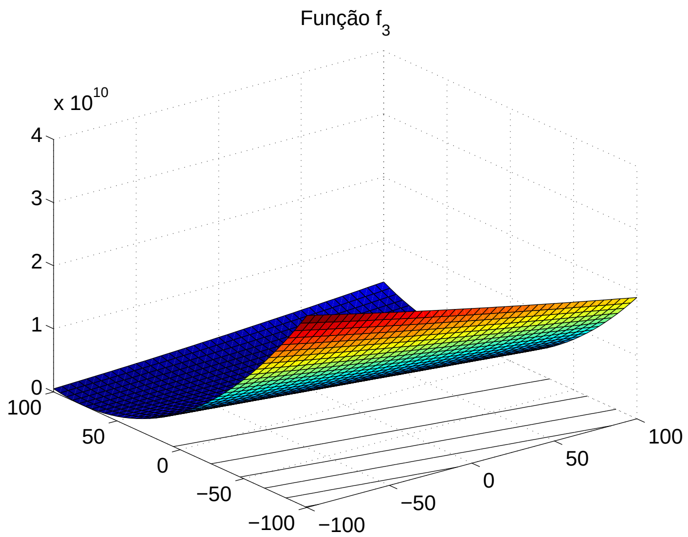

Figura 5.5: Mapa 3D da função f_3.

- Unimodal
- Deslocamento da origem
- Rotacionada
- Não-separável
- Escalonável
- **M** é uma matriz ortogonal qualquer pré-definida
- $\mathbf{x} \in [-100, 100]^D$, Ótimo global: $\mathbf{x}^* = \mathbf{o}$, $F_3(\mathbf{x}^*) = bias_3 = -450$

Função Schwefel 1.2 Deslocada com Ruído

$$f_4(\mathbf{x}) = \left(\sum_{i=1}^{D} \left(\sum_{j=1}^{i} z_j \right)^2 \right) * (1 + 0.4\,|N(0,1)|) + bias_4$$

$$\mathbf{z} = \mathbf{x} - \mathbf{o}, \mathbf{x} = [x_1, x_2, \cdots, x_D]$$

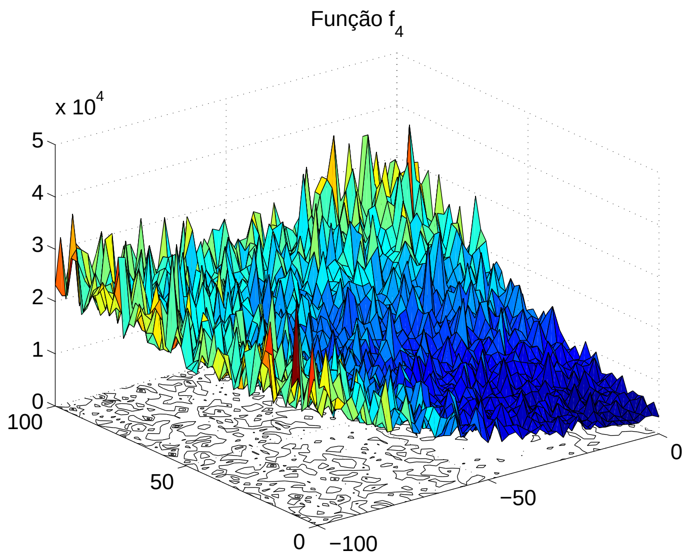

Figura 5.6: Mapa 3D da função f_4.

- Unimodal
- Deslocamento da origem
- Não-separável
- Escalonável
- Ruído aleatório
- $\mathbf{x} \in [-100, 100]^D$, Ótimo global: $\mathbf{x}^* = \mathbf{o}$, $F_4(\mathbf{x}^*) = bias_4 = -450$

Função Schwefel 2.6

$$f_5(\mathbf{x}) = max\{|\mathbf{A_i x} - \mathbf{B_i}|\} + bias_5$$

A é uma matriz DxD, onde a_{ij} são números inteiros aleatórios no intervalo $[-500, 500]$, $\det(\mathbf{A}) \neq 0$, $\mathbf{A}_i$ é a i-ésima linha de **A**.

$\mathbf{B}_i = \mathbf{A}_i * \mathbf{o}$, **o** é um vetor $Dx1$, onde o_i é um número aletório no intervalo $[-100, 100]$.

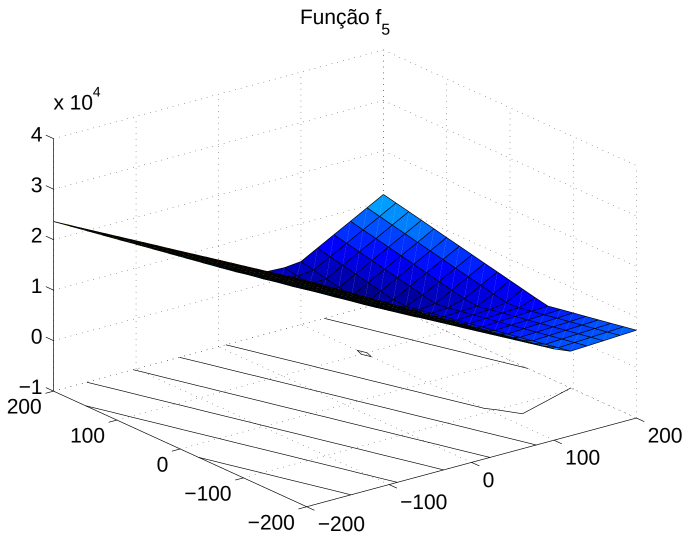

Figura 5.7: Mapa 3D da função f_5.

- Unimodal
- Não-separável
- Escalonável
- Ótimo global na borda do domínio
- $\mathbf{x} \in [-100, 100]^D$, Ótimo global: $\mathbf{x}^* = \mathbf{o}$, $F_5(\mathbf{x}^*) = bias_5 = -310$

Função Rosenbrock Deslocada

$$f_6(\mathbf{x}) = \sum_{i=1}^{D}\left(100\left(z_i^2 - z_{i+1}\right)^2 + (z_i - 1)^2\right) + bias_6$$

$$\mathbf{z} = \mathbf{x} - \mathbf{o} + 1, \mathbf{x} = [x_1, x_2, \cdots, x_D]$$

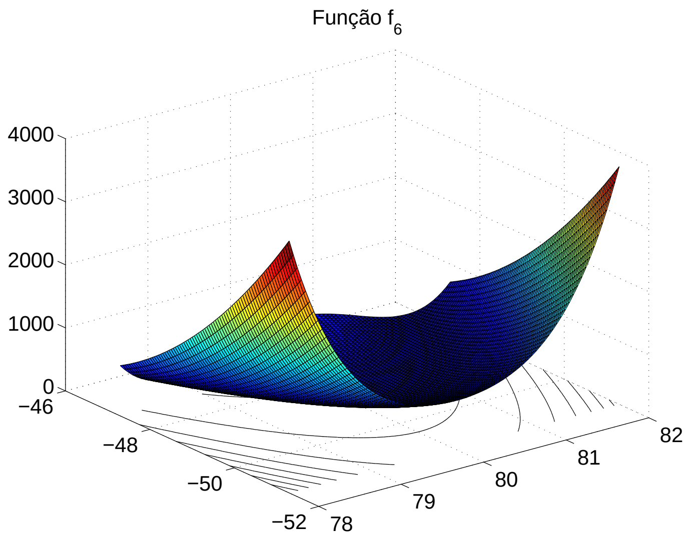

Figura 5.8: Mapa 3D da função f_6.

– Multi-modal
– Deslocamento da origem
– Não-separável
– Escalonável
– Esta função tem um vale muito estreito entre o mínimo local e o mínimo global
– $\mathbf{x} \in [-100, 100]^D$, Ótimo global: $\mathbf{x}^* = \mathbf{o}$, $F_6(\mathbf{x}^*) = bias_6 = 390$

Função Ackley Rotacionada e Deslocada

$$f_8(\mathbf{x}) = -20\exp\left(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D} z_i^2}\right) - \exp\left(\frac{1}{D}\sum_{i=1}^{D}\cos(2\pi z_i)\right) + 20 + e + bias_8$$

$$\mathbf{z} = (\mathbf{x} - \mathbf{o}) \cdot \mathbf{M}, \mathbf{x} = [x_1, x_2, \cdots, x_D]$$

M é uma matriz de transformação linear com um número de condição igual a 100.

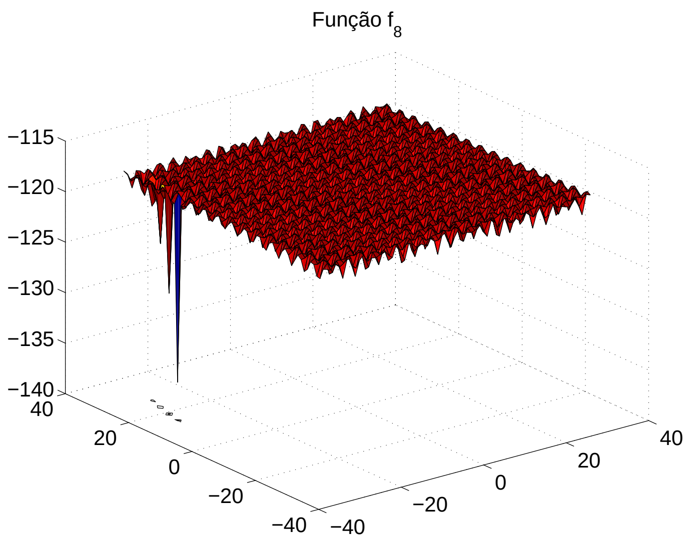

Figura 5.9: Mapa 3D da função f_8.

- Multi-modal
- Deslocamento da origem
- Rotacionada
- Não-separável
- Escalonável
- Ótimo global na borda do domínio
- $\mathbf{x} \in [-32, 32]^D$, Ótimo global: $\mathbf{x}^* = \mathbf{o}$, $F_8(\mathbf{x}^*) = bias_8 = -140$

Função Rastrigin Deslocada

$$f_9(\mathbf{x}) = \sum_{i=1}^{D} \left(z_i^2 - 10\cos(2\pi z_i) + 10 \right) + bias_9$$

$$\mathbf{z} = \mathbf{x} - \mathbf{o}, \mathbf{x} = [x_1, x_2, \cdots, x_D]$$

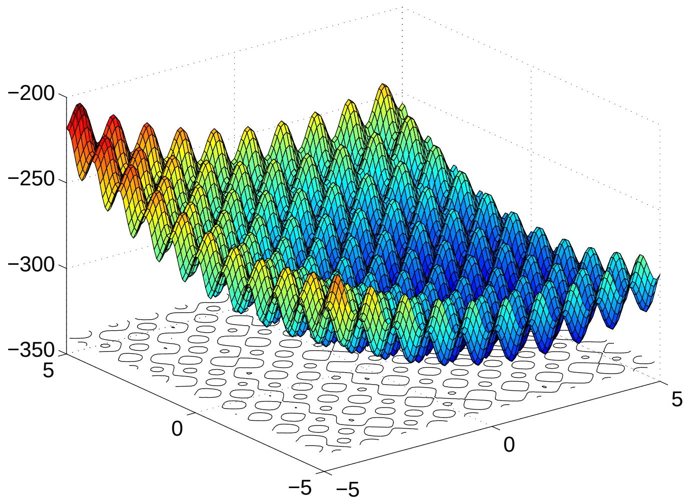

Figura 5.10: Mapa 3D da função f_9.

- Multi-modal
- Deslocamento da origem
- Separável
- Escalonável
- Grande número de ótimos locais
- $\mathbf{x} \in [-5, 5]^D$, Ótimo global: $\mathbf{x}^* = \mathbf{o}$, $F_9(\mathbf{x}^*) = bias_9 = -330$

Função Rastrigin Deslocada e Rotacionada

$$f_{10}(\mathbf{x}) = \sum_{i=1}^{D} \left(z_i^2 - 10\cos(2\pi z_i) + 10 \right) + bias_{10}, [-5, 5]^D$$

$$\mathbf{z} = (\mathbf{x} - \mathbf{o}) \cdot \mathbf{M}, \mathbf{x} = [x_1, x_2, \cdots, x_D]$$

M é uma matriz de transformação linear com um número de condição igual a 2.

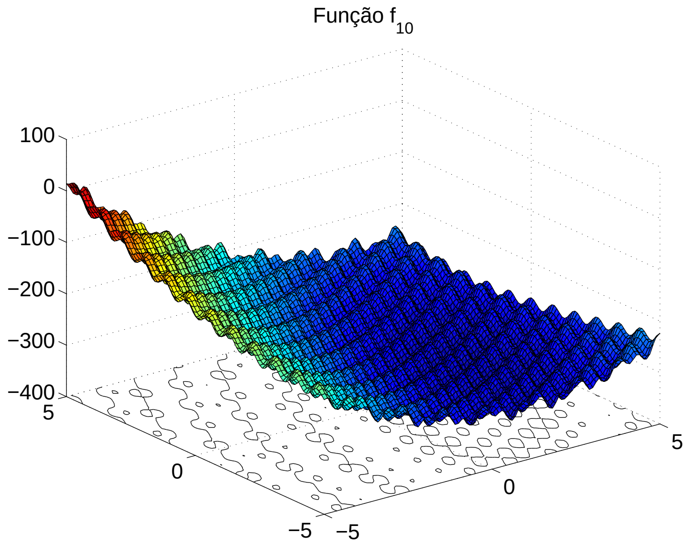

Figura 5.11: Mapa 3D da função f_{10}.

- Multi-modal
- Deslocamento da origem
- Rotacionada
- Não-Separável
- Escalonável
- Grande número de ótimos locais
- $\mathbf{x} \in [-5, 5]^D$, Ótimo global: $\mathbf{x}^* = \mathbf{o}, F_{10}(\mathbf{x}^*) = bias_{10} = -330$

Função Weierstrass Deslocada e Rotacionada

$$f_{11}(\mathbf{x}) = \sum_{i=1}^{D}\left(\sum_{k=0}^{20}\left[0.5^k \cos\left(2\pi 3^k (z_i + 0.5)\right)\right]\right) - D\sum_{k=0}^{20}\left[0.5^k \cos\left(2\pi 3^k \cdot 0.5\right)\right] + bias_{11}$$

$$\mathbf{z} = (\mathbf{x} - \mathbf{o}) \cdot \mathbf{M}, \mathbf{x} = [x_1, x_2, \cdots, x_D]$$

M é uma matriz de transformação linear com um número de condição igual a 5.

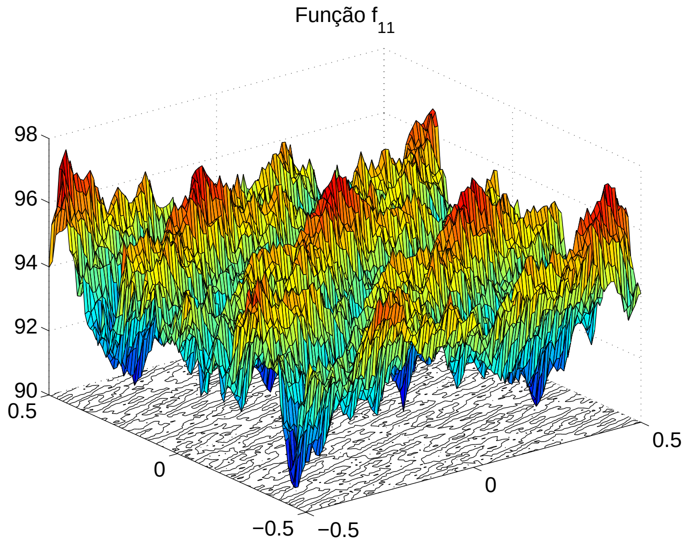

Figura 5.12: Mapa 3D da função f_{11}.

- Multi-modal
- Deslocamento da origem
- Rotacionada
- Não-Separável
- Escalonável
- Função contínua mas diferenciável apenas em alguns pontos
- $\mathbf{x} \in [-0.5, 0.5]^D$, Ótimo global: $\mathbf{x}^* = \mathbf{o}$, $F_{11}(\mathbf{x}^*) = bias_{11} = 90$

Função Schwefel 2.13

$$f_{12}(\mathbf{x}) = \sum_{i=1}^{D} (\mathbf{A_i} - \mathbf{B_i}(\mathbf{x}))^2 + bias_{12}$$

$$\mathbf{A}_i = \sum_{j=1}^{D} \left(a_{ij} \sin \alpha_j + b_{ij} \cos \alpha_j\right)$$

$$\mathbf{B}_i(x) = \sum_{j=1}^{D} \left(a_{ij} \sin x_j + b_{ij} \cos x_j\right), i = 1, \cdots, D$$

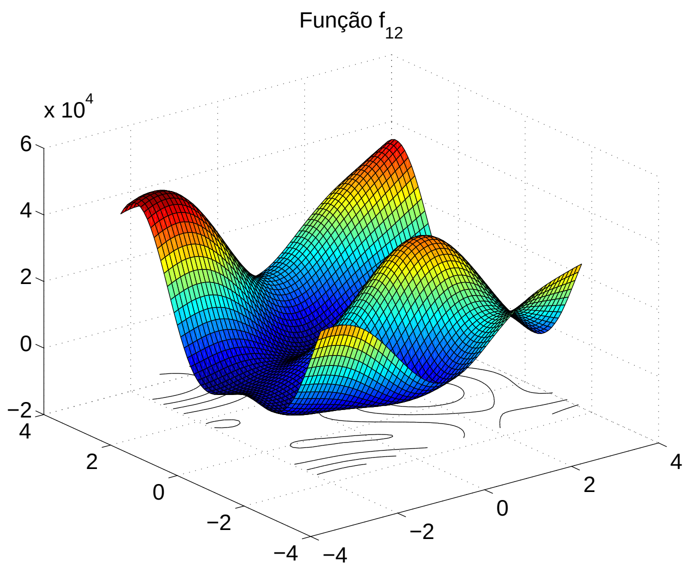

Figura 5.13: Mapa 3D da função f_{12}.

- Multi-modal
- Deslocamento da origem
- Não-Separável
- Escalonável
- $\mathbf{x} \in [-\pi, \pi]^D$, Ótimo global: $\mathbf{x}^* = \alpha, F_{12}(\mathbf{x}^*) = bias_{12} = -460$

Função Griewank e Rosenbrock Expandida e Deslocada

Considerando-se as funções:

F8 - Função Griewank : $F8(x) = \sum_{i=1}^{D} \frac{x_i^2}{4000} - \prod_{i=1}^{D} \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$

F2 - Função Rosenbrock : $F2(x) = \sum_{i=1}^{D-1} \left(100\left(x_i^2 - x_{i+1}\right)^2 + (x_i - 1)^2\right)$

$$f_{13}(\mathbf{x}) = F8(F2(z_1, z_2)) + F8(F2(z_2, z_3)) + \cdots + F8(F2(z_{D-1}, z_D)) + F8(F2(z_D, z_1)) + bias_{13}$$

$$\mathbf{z} = \mathbf{x} - \mathbf{o} + 1, \mathbf{x} = [x_1, x_2, \cdots, x_D]$$

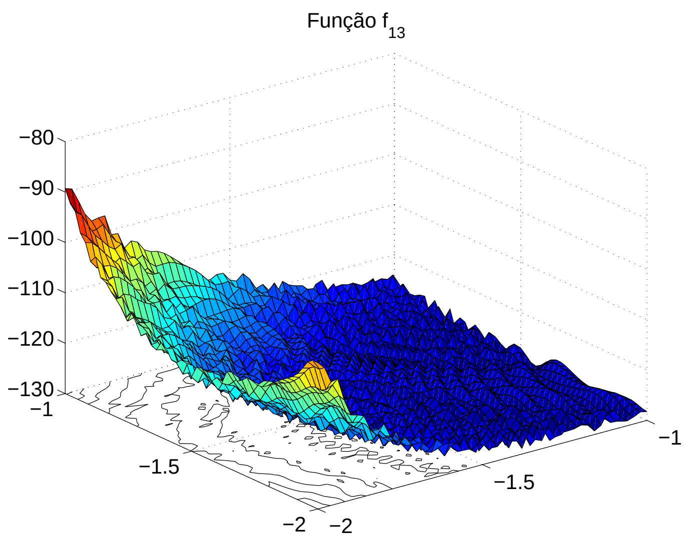

Figura 5.14: Mapa 3D da função f_{13}.

– Multi-modal

– Deslocamento da origem

– Não-separável

– Escalonável

– $\mathbf{x} \in [-5, 5]^D$, Ótimo global: $\mathbf{x}^* = \mathbf{o}$, $F_{13}(\mathbf{x}^*) = bias_{13} = -130$

Função F6 Expandida, Rotacionada e Deslocada

Considerando-se a função:

$$F(x,y) = 0.5 + \frac{\left(\sin^2\left(\sqrt{x^2+y^2}\right) - 0.5\right)}{\left(1 + 0.001\,(x^2+y^2)\right)^2}$$

$$f_{14}(\mathbf{x}) = F(z1, z2) + F(z_2, z_3) + \cdots + F(z_{D-1}, z_d) + F(z_D, z_1) + bias_{14}$$

$$\mathbf{z} = (\mathbf{x} - \mathbf{o}) \cdot \mathbf{M}, \mathbf{x} = [x_1, x_2, \cdots, x_D]$$

M é uma matriz de transformação linear com um número de condição igual a 5.

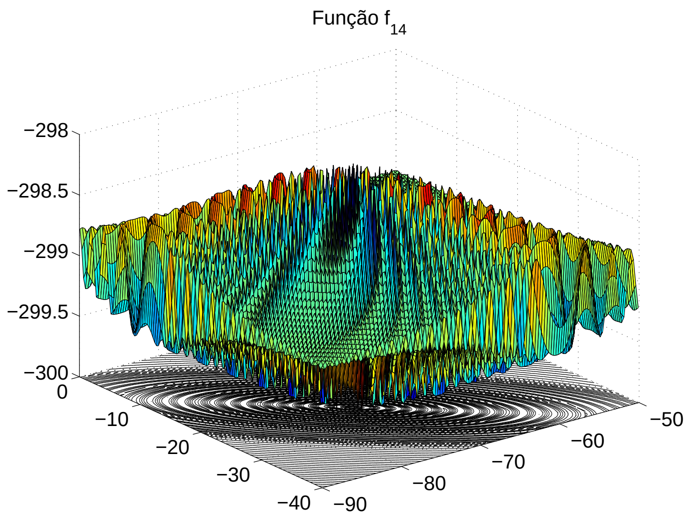

Figura 5.15: Mapa 3D da função f_{14}.

- Multi-modal
- Deslocamento da origem
- Não-separável
- Escalonável
- $\mathbf{x} \in [-100, 100]^D$, Ótimo global: $\mathbf{x}^* = \mathbf{o}$, $F_{14}(\mathbf{x}^*) = bias_{14} = -300$

Anexo 2

Funções para Medida de Desempenho

Função Sphere

$$f_{Sphere}(\mathbf{x}) = \sum_{i=1}^{D} x_i^2$$

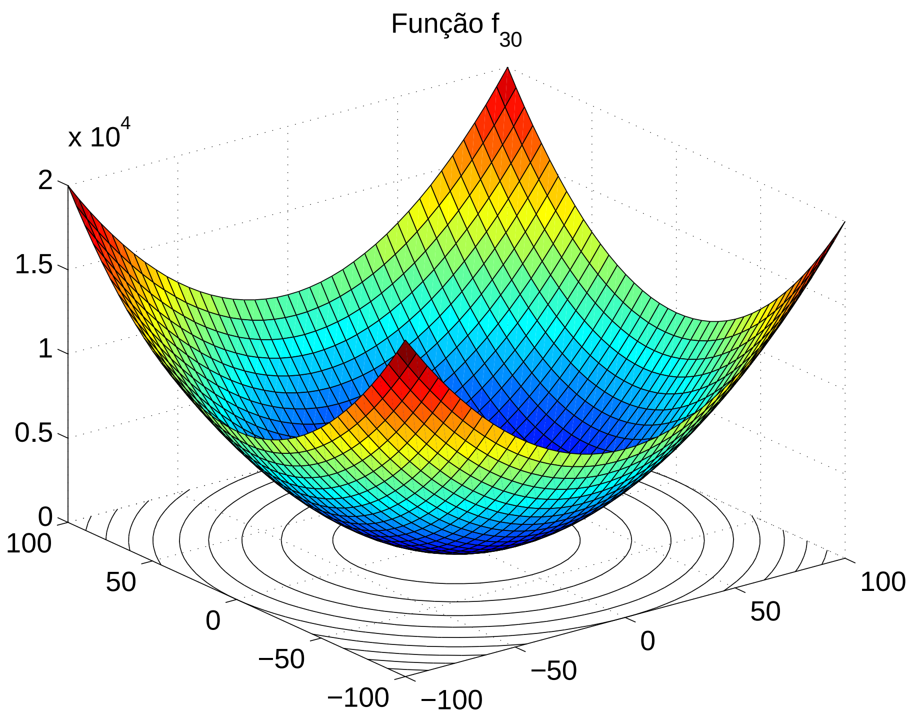

Figura 5.16: Mapa 3D da função f_{Sphere}.

– Unimodal

– $\mathbf{x} \in [-100, 100]^D$, Ótimo global: $\mathbf{x}^* = \mathbf{0}$, $f_{Sphere}(\mathbf{x}^*) = 0$

Função Ackley

$$f_{Ackley}(\mathbf{x}) = -20\exp\left(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D}x_i^2}\right) - \exp\left(\frac{1}{D}\sum_{i=1}^{D}\cos(2\pi x_i)\right) + 20 + e$$

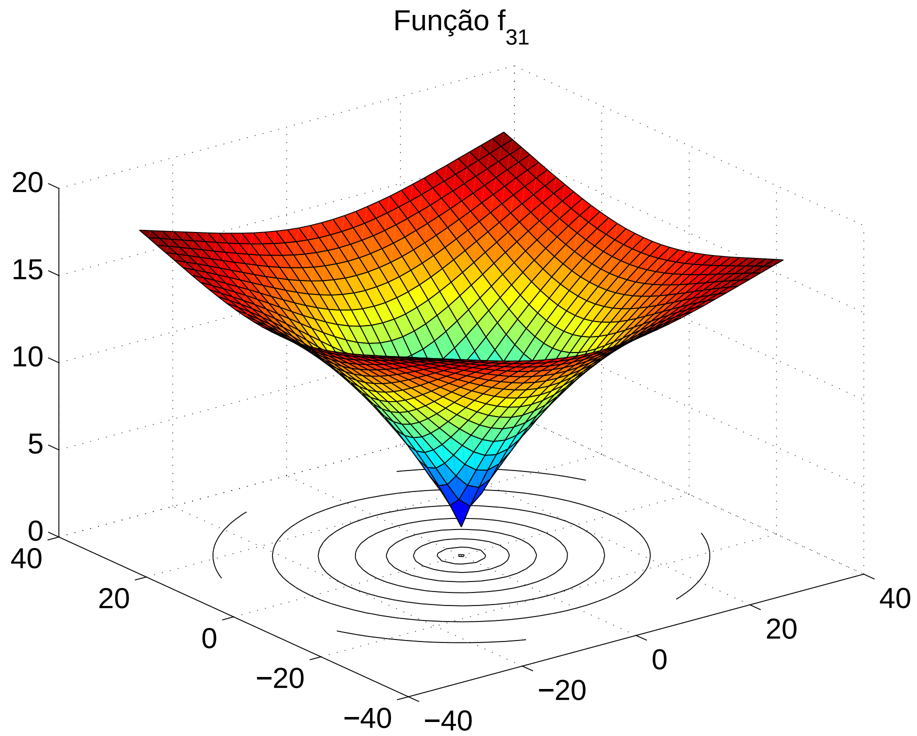

Figura 5.17: Mapa 3D da função f_{Ackley}.

– Multi-modal

– $\mathbf{x} \in [-32, 32]^D$, Ótimo global: $\mathbf{x}^* = \mathbf{0}$, $f_{Ackley}(\mathbf{x}^*) = 0$

Função Griewank

$$f_{Griewank}(\mathbf{x}) = \frac{1}{4000}\sum_{i=1}^{D} x_i^2 - \prod_{i=1}^{D}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$$

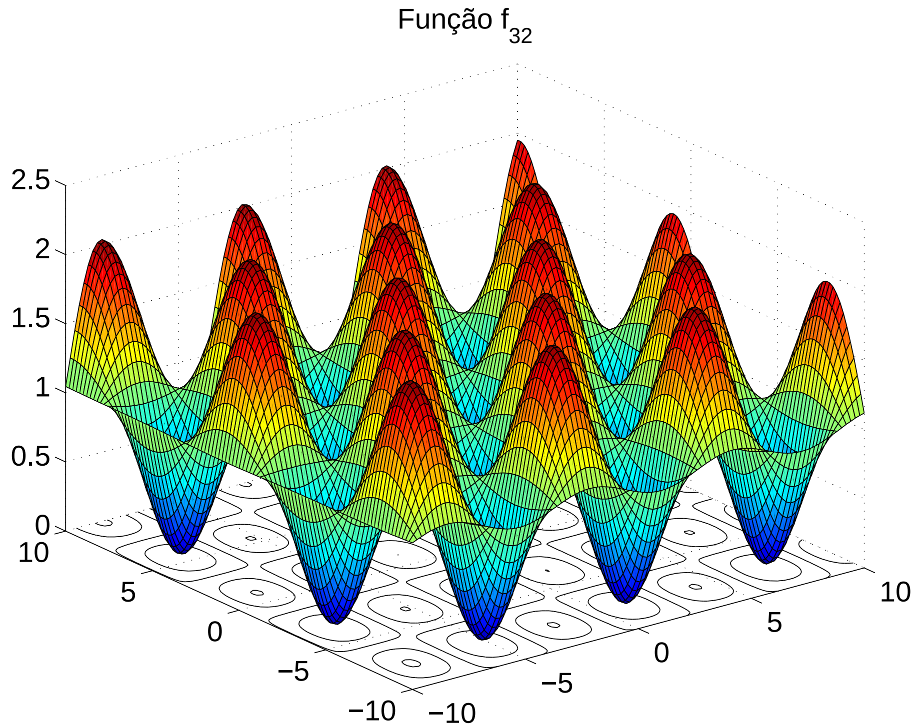

Figura 5.18: Mapa 3D da função $f_{Griewank}$.

- Multi-modal
- $\mathbf{x} \in [-600, 600]^D$, Ótimo global: $\mathbf{x}^* = \mathbf{0}$, $f_{Griewank}(\mathbf{x}^*) = 0$

Função Rastrigin

$$f_{Rastrigin}(\mathbf{x}) = \sum_{i=1}^{D} \left[x_i^2 - 10\cos(2\pi x_i) + 10 \right]$$

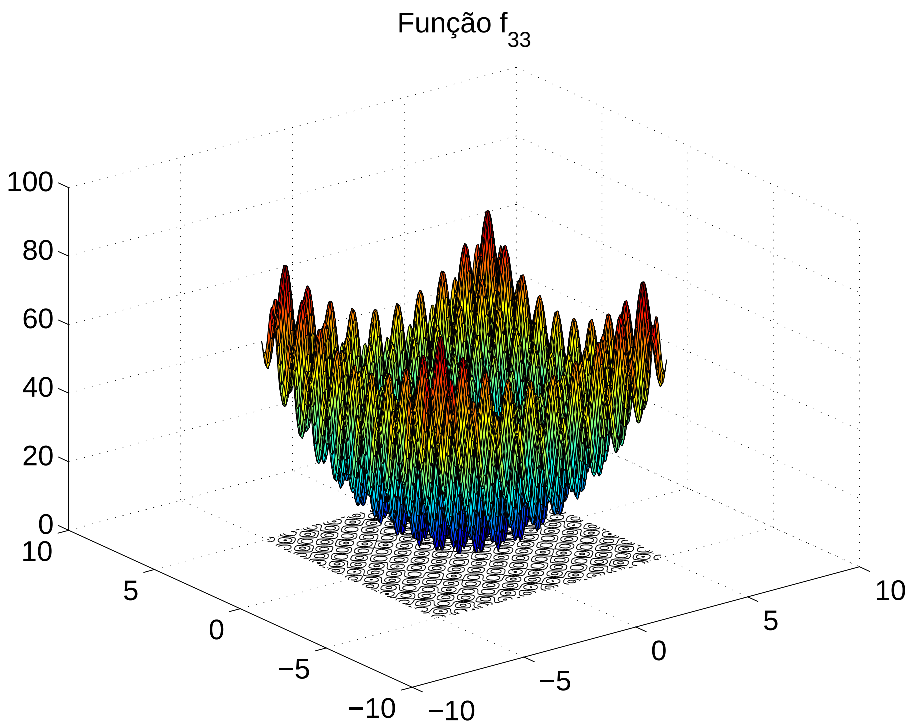

Figura 5.19: Mapa 3D da função $f_{Rastrigin}$.

– Multi-modal

– $\mathbf{x} \in [-5.12, 5.12]^D$, Ótimo global: $\mathbf{x}^* = \mathbf{0}$, $f_{Rastrigin}(\mathbf{x}^*) = 0$

Função Schwefel 2.26

$$f_{Schwefel}(\mathbf{x}) = -\sum_{i=1}^{D}\left(x_i \sin\left(\sqrt{|x_i|}\right)\right) + 12569.5$$

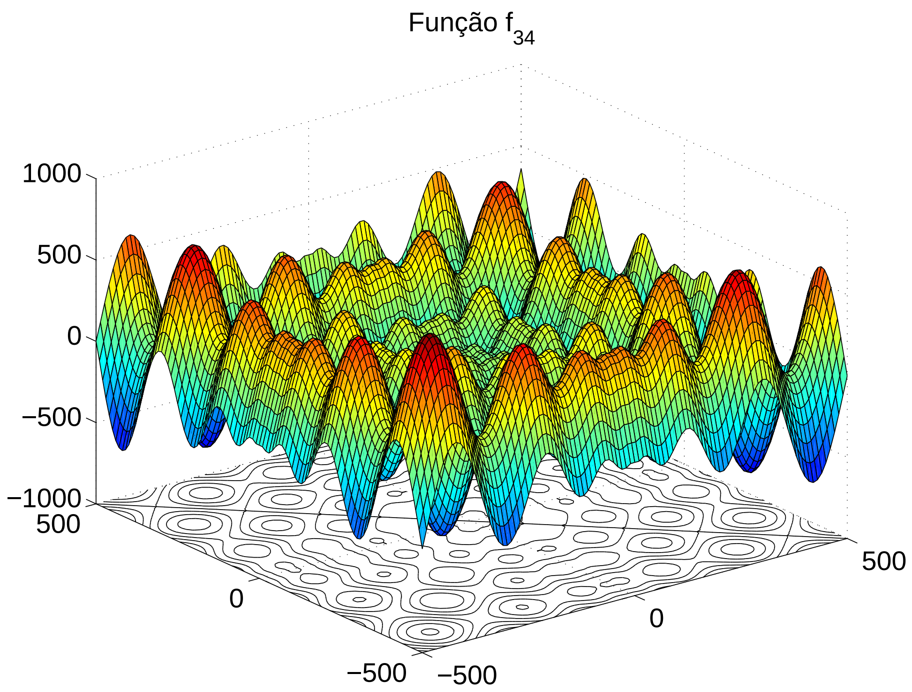

Figura 5.20: Mapa 3D da função $f_{Schwefel}$.

- Multi-modal
- $\mathbf{x} \in [-500, 500]^D$, Ótimo global: $\mathbf{x}^* = \mathbf{420.9687}$, $f_{Schwefel}(\mathbf{x}^*) = 0$

Função Rosenbrock

$$f_{Rosenbrock}(\mathbf{x}) = \sum_{i=1}^{D-1} \left[100 \left(x_{i+1} - x_i^2 \right)^2 + (x_i - 1)^2 \right]$$

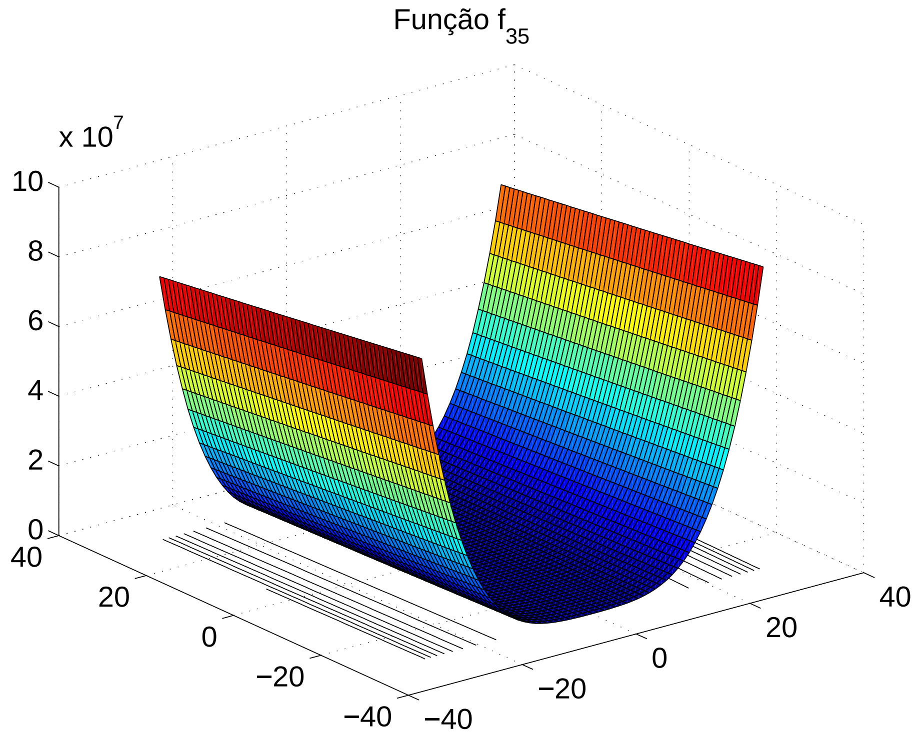

Figura 5.21: Mapa 3D da função $f_{Rosenbrock}$.

– Multi-modal
– $\mathbf{x} \in [-30, 30]^D$, Ótimo global: $\mathbf{x}^* = \mathbf{1}$, $f_{Rosenbrock}(\mathbf{x}^*) = 0$