Model Discrimination Design Generation for Accelerated Life Testing Experiments via Hybridized Optimization Algorithms

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Fidalgo   Arrhenius   Meeker

MMM vs. MM under pharmacokinetic model (López-Fidalgo et al., 2007)

Select Calculate Options ❷

Divergence Method:

Closed-Form ▾

Select Distribution: ❸

Log-Normal ▾

⏱ Design Space Bound Settings ❹

Support Points:

1		3							10

1 2 3 4 5 6 7 8 9 10

Lower Bound: **Upper Bound:**

0.1   5

🧪 True Model Mean Response Parameters ❺

ζ_1 : ζ_2 : ζ_3 :

1   1   1

🎯 Dispersion Parameter

Dispersion (σ):

1

⚔ Rival Model Mean Response Parameters Bound

δ_1 **Lower:** δ_1 **Upper:**

0.1   100

δ_2 **Lower:** δ_2 **Upper:**

0.1   100

⚙ Algorithm Settings ❻

Outer PSO Particles: **Outer PSO Iterations:**

64   5

☐ Use Inner PSO

BFGS Retries:

2

🚀 **Run Optimization**

Result   Setting

🔍 Model Discrimination

True Model:	Rival Model: ❶
$\dfrac{\zeta_1 \cdot x}{\zeta_2 + x} + \zeta_3\, x$	$\dfrac{\delta_1 \cdot x}{\delta_2 + x}$

The goal of this design is to discriminate between the true model and a competing rival model by maximizing the divergence between them over the design space.

The general objective function is given by:

$$\max_{\xi \in \Xi} \mathrm{KL}_{r,tr}(\xi) = \max_{\xi \in \Xi} \min_{\theta_r \in \Theta_r} \int_X D_{\mathrm{KL}}(M_{tr}, M_r, x, \theta_r)\xi(dx)$$

Formally, the optimal design criterion value is defined as:

$$C^* = \arg\max_{\xi \in \Xi} \min_{\theta_r \in \Theta_r} \left\{ \int_X \sum_{i=1}^{n} w_i \cdot D_{\mathrm{KL}}\left(M_{tr}(x_i, \theta_{tr}), M_r(x_i, \theta_r)\right)\xi(dx) \right\}$$

📌 Approximation Design ❶

Support Point	Weight
0.10	0.53
2.48	0.32
5.00	0.15

📊 Criterion Value and CPU Time ❷

Criterion_Value	CPU_Time
0.014864	18.48

📐 Model Parameters ❸

True Model Parameters

ζ_1	ζ_2	ζ_3	σ
1.00	1.00	1.00	1.00

Rival Model Parameters

δ_1	δ_2	σ
18.56	11.31	1.00

📈 Directional Derivative Plot ❹

Directional Derivative