Model-based bioequivalence analysis of pharmacokinetic crossover trials compared to standard non-compartmental analysis IS IDEROT

Inserm

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Context

- Crossover trials with two periods and two sequences
- Standard approach (FDA^[1] and EMEA^[2])
- Compute AUC and C_{max} by non compartmental analysis
- Test on log parameters
- Using linear mixed effects model with treatment, period, sequence, and subject effects Needs >10 samples per subject
- Nonlinear mixed effects models (NLMEM)^[3,4]
- Simultaneous data analysis for all subjects
- \diamond Few samples per subject \rightarrow study on patients

Objectives: mimick the standard bioequivalence analysis using NLMEM and Wald test

Methods

- NLMEM bioequivalence analysis mimicking NCA analysis
 - Statistical model
 - Parametric pharmacokinetic (PK) model
 - Eetween (BSV) and within subject variability (WSV) on all PK parameters
 - Treatment (β), period, and sequence effects on all PK parameters
 - Parameter estimation by maximum likelihood
 - SAEM algorithm implemented in MONOLIX 2.4^[5,6]

Bioequivalence Wald test

- ♦ Schuirmann's test^[7] H₀: { $\beta \le \log(0.8)$ or $\beta \ge \log(1.25)$ }
- × Rejection of H₀: CI_{90%}($\hat{\beta}$) ∈ [log(0.8); log(1.25)]
- CI90% computed from the estimated treatment effect and its standard error (SE)

Wald test on secondary parameters^[8]

- × β_{AUC} = − $\beta_{CL/F}$ (linear PK) → SE(β_{AUC}) =SE($\beta_{CL/F}$)
- × $β_{Cmax}$: nonlinear function of fixed effects → estimation of SE($β_{Cmax}$) by delta method^[9] or by simulation using the parameter estimates and the Fisher information matrix estimate

Simulation study

× Rich: N=40, n=10

- One-compartment model (parameters k_a, CL/F, V/F)
- \diamond Crossover trials with two periods and two sequences

Designs

▼ Original: N=12, n=10

▼ Sparse: N=40, n=3

- ▼ Intermediate: N=24, n=5
- Treatment effect on CL/F and V/F
- 1000 simulations under $H_{0,80}$: $\beta_{CL/F}$ =log(0.8) and $\beta_{V/F}$ =log(0.8)
- ★ 1000 simulations under $H_{0,125}$: $\beta_{CL/F}$ =log(1.25) and $\beta_{V/F}$ =log(1.25)
- Two levels of variability



▼ S_{1,1} and S_{h,1}: simulations with the 4 designs

$\mathbf{x} \mathbf{S}_{\mathbf{h},\mathbf{h}}$: simulations with the intermediate design Concentrations (ng/ml) simulated with the four design.



⁺ Evaluation of the estimates for $H_{0.80}$

- \diamond Geometric mean of AUC and C_{max} for the reference treatment compared to the population simulated parameters
- β_{AUC} and β_{Cmax} compared to the simulated value
- SE(β_{AUC}) and SE(β_{Cmax}) compared to the empirical SE (standard deviation of the 1000 treatment effect estimates)
- Type I error estimation: proportion of rejected H₀

Wald test performed with the estimated and empirical SE

[1] FDA. Guidance on statistical approaches to establishing bioequivalence (2001) [2] EMEA. Guidance on investigation of bioavailability and bioequivalence (2001) [3] Dubois A, Gsteiger S, Pigeolet E and Mentré F. Pharmaceutical Research. 27 (2010) [4] Panhard X, Taburet AM, Piketti C and Mentré F. Statistics in Medicine. 26 (2007)



Results



- NLMEM: no bias even for sparse design
- $\beta_{\rm AUC}$ and $\beta_{\rm Cmax}$, SE($\beta_{\rm AUC}$) and SE($\beta_{\rm Cmax}$)







- Good estimation of the treatment effect for NCA and NLMEM
- Underestimation of the SE increasing when large variability

Type I error versus the design for AUC and Cma



- \diamond NCA: type I error at 5% except for C_{max} with the sparse design and for S_{h,h} ♦ NLMEM

 - Type I error at 5% for the rich design but inflation when N or n decreases
- Correction of the inflation by the use of the empirical SE

Conclusion

- Bioequivalence analysis by NCA
- \diamond Bias in the geometric means of AUC and C_{max} for sparse design
- Good properties of the test except for high variability
- Bioequivalence analysis by NLMEM
 - Good estimation of the population estimates even for sparse design
 - ♦ Good properties of the test for rich design (asymptotic conditions)
 - Correction of the test for small sample size needed (linked to the underestimation of the SE)
 - \diamond Applicable to nonlinear pharmacokinetics (biologic drugs) and to sparse design

[5] Kuhn E and Lavielle M. ESAIM Probability and Statistics. 8 (2004)

[9] Oehlert GW. The American Statistician. 46 (1992)

[6] www.monolix.org [7] Schuirmann DJ, Journal of Pharmacokinetics and Biopha eutics, 15 (1987) [8] Dubois A, Lavielle M, Gsteiger S, Pigeolet E and Mentré F. sub

- **×** NLMEM: similar estimation of SE(β_{Cmax}) by delta method and simulation
- Type I error

