

INTRODUCTION

- **Nonlinear mixed effect modeling or population analysis**
 - pharmacokinetic (PK) /pharmacodynamic (PD) data
- **Population analyses often based on limited sampling strategy**
 - ethical and / or financial reasons
- **Methodology developed to ensure informative population design**
 - based on the Fisher information matrix (MF)
 - expression of MF using a first order Taylor expansion of the model
- **Implementation in a R function PFIM [1]**
 - R function for population design evaluation and optimization
- **Recent extensions of PFIM (released in March 2011)**
 - for multiple response models [2]
 - Implementation in a new interface version PFIM Interface 3.1
 - for models with parameters quantifying influence of discrete covariates [3]
 - for models including within-subject variability [4]
 - Implementation in a new R script version PFIM 3.2 (last version PFIM 3.2.2)
 - => **Other features for both versions**
 - inclusion of libraries of PK and PD models with their documentation
 - computation of the block or the complete MF

OBJECTIVES

To illustrate the use of PFIM Interface 3.1 and PFIM 3.2 on warfarin PKPD

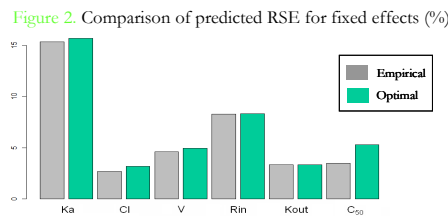
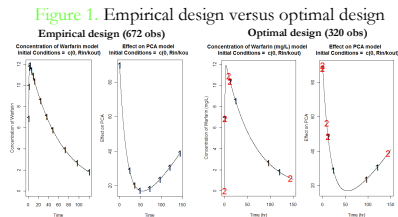
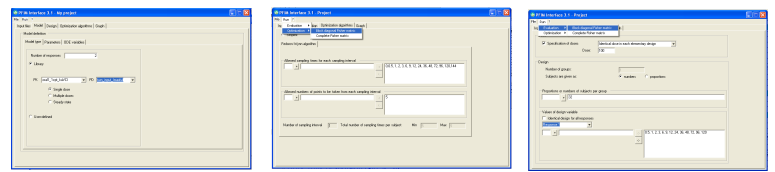
JOINT PKPD MODEL OF WARFARIN

- **PK: total racemic warfarin plasma concentration**
 - single oral dose of 100 mg
 - one compartment model, first order absorption and elimination
 - exponential modeling of the random effects
- **PD: effect on prothrombin complex activity (PCA)**
 - turnover model with inhibition of the input
 - exponential modeling of the random effects

PFIM Interface 3.1

Joint PKPD design on warfarin

- **Evaluation of the empirical design**
 - one group of 32 subjects
 - 13 sampling times for PK and 7 sampling times for PD
- **Design optimization with the Federov-Wynn algorithm**
 - 32 subjects with only 5 sampling times per subject (common to both responses)
 - sampling times from empirical design (PK + PD)



→ Relative standard errors (RSE) in the same range for the fixed effects
 → 2.1 less samples with optimal design than empirical design

PFIM 3.2

Pharmacogenetic on warfarin PK

- **Single nucleotide polymorphism (SNP) CYP2C9**
 - SNP on the gene of a cytochrome involved in the warfarin metabolism
 - influence of the genetic covariate on the clearance
 - clearance decrease of 50% for subjects with a mutant genotype
- **Evaluation of the optimized PK/PD design with the effect of the genetic covariate on clearance**
 - predicted power of the comparison Wald test (type I error=5%)
 - number of subjects needed (given power=90%)

Table 1. Covariate effect parameters

Covariate	Parameter Associated	Categories	Proportions of subjects in each category (%)	β
CYP2C9	CL	Wild genotype (ref)	60	$\log(0.5)=-0.69$ or $\log(0.8)=-0.22$
		Mutant genotypes	40	

Figure 3. Empirical design evaluation output

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covariate model :
  NB: covariates are additive on log parameters
  Covariate 1 : cyp ( c1 )
  Categories References Proportions
  (1) W = 0.6
  (2) M = 0.4

***** EXPECTED STANDARD ERRORS *****
----- Fixed Effects Parameters -----
      Beta  STdeffor  RSE
ka  1.6000000  0.250716480  15.669780 %
v   8.0000000  0.234637330  3.182973 %
c1  0.1300000  0.008119389  6.245684 %
rin  5.4000000  0.450993467  8.335064 %
kout 0.0600000  0.001999504  3.322506 %
c50  1.2000000  0.059443091  4.953591 %
beta_c1_CYP_M -0.6931472  0.101924601  14.704612 %

***** COMPARISON TEST *****
      Beta  95 % CI  exp(beta)  95 % CI
beta_c1_CYP_M -0.6931472 [-0.893; -0.493]  0.5 [0.409; 0.611]

Type I error = 0.05
beta_c1_CYP_M Expected_power Number_subjects_needed (for a given power=0.9)
              0.999999 7.270317
    
```

Covariate model
 (W=wild, M=mutant)

Standard error and RSE of the genetic covariate effect on clearance

95% confidence interval of the covariate effect

Expected power and number of subjects needed for the comparison Wald test

Table 2. Results on genetic covariate effect

β	SE (RSE %)	95% CI(β)	exp(β)	95% CI(exp(β))	Expected power	Number of subjects needed
-0.69	0.10 (15)	[-0.89; -0.49]	0.50	[0.41; 0.61]	1	8
-0.22	0.10 (43)	[-0.41; -0.03]	0.80	[0.66; 0.97]	0.63	64

Interaction of drug X on warfarin PK in crossover trial

Planification of a new study to assess the absence of interaction of drug X on warfarin ka

- two-period, two-sequence balanced crossover trial
- inter-occasion variability on ka: $\gamma_{ka}^2=0.3$ (CV=55%)
- expected effect of the co-medication on ka: $\beta=\log(1)=0$

- **Evaluation of the empirical PK design**
 - 32 subjects
 - sampling times
 - 0.5, 1, 2, 3, 6, 9, 12, 24, 36, 48, 72, 96 and 120 hours
 - Predicted power of the bioequivalence Wald test (type I error=5%)
 - Number of subjects needed (given power=90%)

Figure 4. Empirical design evaluation output

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covariate model :
  NB: covariates are additive on log parameters
  Covariates changing with occasion
  Covariate 1 : comed ( ka )
  Categories References Proportions
  (1) W = 0.5
  (2) X = 0.5

***** EXPECTED STANDARD ERRORS *****
----- Fixed Effects Parameters -----
      Beta  STdeffor  RSE
ka  1.90  0.28895018  18.06001 %
v   8.00  0.208783108  2.609789 %
beta_ka_comed_x 0.00  0.144882923  Inf %

----- variance of Inter-Subject Random Effects -----
      Omega  STdeffor  RSE
ka  0.70  0.21085522  31.66907 %
v   0.02  0.00582822  27.24806 %
c1  0.06  0.010606907  26.77818 %

----- variance of Inter-occasion Random Effects -----
      Gamma  STdeffor  RSE
ka  0.3  0.07139004  23.70666 %

***** EQUIVALENCE TEST *****
      Beta  90 % CI  exp(beta)  90 % CI
beta_ka_comed_x 0 [-0.238; 0.238]  1 [0.785; 1.293]

Type I error = 0.05
beta_ka_comed_x Expected_power Number_subjects_needed (for a given power=0.9)
              0.4583113 115.5273
    
```

Covariate model
 (W=warfarin, X=warfarin+drug X)

Standard error and RSE of the co-medication covariate effect on ka

Standard error and RSE of the inter-occasion variability

90% confidence interval of the covariate effect

Expected power and number of subjects needed for the bioequivalence Wald test

CONCLUSION

- PFIM Interface 3.1 and PFIM 3.2 freely available at www.pfim.biostat.fr
- **Great potential of these tools to evaluate and/or optimize designs :**
 - for multiple response models
 - for more complex models quantifying the influence of discrete covariate and/or inter-occasion variability.

REFERENCES

- [1] www.pfim.biostat.fr
- [2] Bazzoli C, Retout S and Mentré F. *Computer Methods and Programs in Biomedicine*. 98: 55-65, 2010.
- [3] Retout S, Comets E, Samson A and Mentré F. *Statistics in Medicine*. 26: 5162-5179, 2007.
- [4] Nguyen TT, Bazzoli C and Mentré F. *American Conference in Pharmacometrics*, Mashantucket, United-States, 2009.