Optimal design for TGF beta RI kinase inhibitor

Sophie Glatt, Kayode Ogungbenro and Iva Gueorguieva





Outline

- Background
- Strategy
- TGFb PK/PD model in rats
- Multivariate optimal design
- TGFb PK/PD model & design in human
- Challenges in optimal design from practical point of view





Tumor Cell

- Epithelial-to-mesenchymal transition
- Increased cell motility and invasiveness





Tumor Microenvironment

- Extracellular matrix remodeling
- Activated stromal cells
- Protease activation
- Angiogenesis
- Immunosuppression



Understand PK and determine PKPD relationship in animals: Assist appropriate dose range selection

- Develop PK/PD model in animals using Smad phosphorylation (biomarker)
 - In rats, mouse
- Perform allometric scaling to predict human PK
- Variability of biomarker has been incorporated to assess response variability



Rat Pharmacokinetics



	Parameters	Estimates	95% Cl
Disposition			
	V (L)	1.09	[0.76 ; 1.42]
	CL (L/h)	0.339	[0.23 ; 0.45]
Absorption	KA (h ⁻¹) fixed	8.00	
	F (%)	0.65	[0.49 ; 0.81]
Interanimal variability	ω^2 _{CL}	0.48 (CV=69.6%)	[0.245 ; 0.723]
	$\omega^2 v$	0.64 (CV=80.1%)	[0.335 ; 0.947]
residual error: additive part	µmol/L	64.20	[0.33 ; 0.95]

Indirect Response Models

• Baseline response is maintained by factors controlling response synthesis and degradation



 k_{syn} is a 0 order rate constant k_{out} is a 1^{st} order rate constant

$$\frac{\mathrm{dR}}{\mathrm{dt}} = \mathbf{k}_{\mathrm{syn}} - \mathbf{k}_{\mathrm{out}} \mathbf{R}$$

Summary of PD parameters corresponding to biomarker model (mice)

K _{syn} K _{out}	Denometer	Population mean Estimate	Population mean Estimate	
SMAD SMAD	Parameter			
$I(t)$ $U = C^{\gamma}$	K _{out} (h ⁻¹) I _{MAX}	1.3 (15.8)	2.2 (6.9) 1*	
$I(t) = 1 - \frac{I_{\max} \times C^{\gamma}}{C^{\gamma} + IC_{50}^{\gamma}}$	IC ₅₀ (µM)	0.7 (11.2)	0.8 (7.6)	
$k_{syn} = k_{out} \times pSMAD(\%)$	n	2.5 (17.4)	1*	
pSMAD = 100(fixed)	Additive Residual error (SEE %)	10.6% (28.6)	18.4% (11.9)	

SEE Standard error of the estimate * Fixed

Calu6: Lung cancer cell line; MXI: Brest cancer cell line. t1/2_kout(MX1)=32 min t1/2_kout(Calu6)=18.6 min

Summary of PD parameters corresponding to biomarker model (rats)

	Population mean Estimate	Population mean Estimate
Parameter	(%SEE) Tumor	(%SEE) PBMC
K _{out} (h ⁻¹) I _{MAX}	36.7 (7.3) 0.86 (3.4)	47.4 (1.8) 0.95 (1.1)
$IC_{50}(\mu M)$	0.72 (25.7)	1.96 (13.1)
Proportional Residual error (SEE %)	62.1% (19.9)	70.2% (25.2)

SEE Standard error on the estimate

PBMC: peripheral blood mononuclear cell

Semi-mechanistic model for tumor growth delay



Simeoni, Cancer Res., 2006

Retrospective optimal design in rats

TGF-beta inhibitor pharmacokinetic/pharmacodynamic parameters in rats

	Parameter name	Individual RAT	Population RAT mean [%SEE]
Pharmacokinetic	ka [h ⁻¹]	10	8
	V [L]	0.85	0.9 [15.5]
	CL [L/h]	0.29	0.34 [16.6]
	F [%]	65.3	65 [0.1]
	ω^2_{CL}		0.48 [2.5]
	ω^2_{V}		0.64 [24.3]
	Additive residual error $\sigma_{PK_ADD}^{2}$	64.2	64 [32.9]
Pharmacodynamic	k _{out}	36.7	36.7 [7.3]
	I _{max}	0.86	0.86 [3.4]
	IC50	0.72	0.72 [25.7]
	Proportional residual error $\sigma_{PD_PROP}^{2}$ [%]	62	62[19.9]



Popdes software: Gueorguieva, et al., Computer Method Prog Biomed, 2006 (in preparation)

Rat design constraints

Individual rat

– PK model $y_j = f(\theta, t_j) + \varepsilon_j$

- Three sampling times (j=3)
- Time bounds (0-24h)
- PK/PD model $y_{mj} = f_m(\theta, t_j) + \varepsilon_{mj}$
 - Six sampling times chosen
 - Number of responses (M=2)
 - Response covariance matrix
 - Time bounds (0-24h)

$$\Sigma = \begin{pmatrix} 1 & 0.15 \\ 0.15 & 1 \end{pmatrix}$$

Rat design constraints

• Population rat

- PK model $y_{ij} = f(\theta_i, t_{ij}) + \varepsilon_{ij}$

- Three sampling times (j=3)
- Time bounds (0-24h)
- PK/PD model $y_{imj} = f_m(\theta_i, t_{ij}) + \varepsilon_{imj}$
 - Six sampling times chosen
 - Number of responses (M=2)
 - Response covariance matrix
 - Time bounds (0-24h)

$$\Sigma = \begin{pmatrix} 1 & 0.15 \\ 0.15 & 1 \end{pmatrix}$$

Optimal design for rat individual and rat population TGFb model

Optimiser	Optimal sampling times (h)									
Individual PK	0.1	0.5	3.46							
Individual PK/PD	0.0	0.0	0.5	0.5	3.5	24.0				
Population PK	0.1	1.0	7.1							
Population PK/PD	0.0	0.5	1.75	7.5	18.75	24				
	CVSE ^a [%]									
	ka	CL	V	$\omega^2_{\ CL}$	ω^2_{V}	$\sigma_{PK_2^{ADD}}$	Imax	IC50	kout	$\sigma_{\substack{\text{PD}_{PROP}\\2}}$
		0.32								
Individual PK	0.43		0.16			40.83		\frown		
Individual PK/PD	0.30	0.31	0.12			28.9	20.6	244.6	35.7	126.9
Population PK	0.12	13.5	13.5	45.4	45.4	18.3				
Population PK/PD	0.10	12.4	12.4	33.2	36.0	9.13	1.66	18.8	4.24	11.75

* In all cases Exchange algorithm (Ogungbenro, 2006, Computer Method Prog Biomed) with 0.01 step size was used

Optimal design for individual and population TGFb model

- Individual rat
 - PK
 - Early sampling with last time at 3.5h (due to additive model)
 - small CVSE on structural parameters; larger on additive error (40%);
 - PK/PD:
 - Last sampling at the upper bound (p-SMAD proportional error) and repeating the two early times;
 - Parameter CVSEs <40 with exception of IC50;
- Population rat
 - PK
 - Later last time point (7h)
 - CVSEs < or around 40%
 - PK/PD
 - No repeating time points with more even distribution in time (i.e. requiring samples before and after 12h);
 - Lower CVSEs (compared with individual PK/PD) < or around 30%.

Interspecies allometry

- Using IV PK parameters in rat, mouse and dogs
- Included in the model was an allowance for estimating correlation between animals within a species
- Human clearance predicted to be 20.9 L/h (8.11-53.76).
- Volume of distribution predicted to be 94.57L (44.13-202.69).
- Assumed bioavailability 50% (biopharmaceutics)

Allometric scaling

Allometric scaling for Clearance (L/hr)

Allometric scaling for Volume (L)



Clearance (L/hr)

PK/PD model



Design first in human studies

Based on simulations

• Based on D-optimal design

Simulations in humans

- Preclinical data suggest that
 - 30% inhibition of pSMAD over 24 hours and at least 50% inhibition at tmax (time at maximum inhibition) is required for tumor growth delay
- Simulation in humans were performed in order to achieve this level of inhibition
- Simulation used both cell lines, used allometric scaling for PK using mouse, rat and dog.
- Variability of the biomarker was incorporated in the simulations

From rat model : Simulated human PD and 90%CI profiles after QD and BID administrations



D-optimal design in human

Design		Optimal sampling times (h)							
Individual PK	0.0	0.75	24.0						
	0.0	0.75	27.0						
Individual PK/PD	0.0	0.0	0.8	0.8	24	24			
				CVS	E ^a [%]				
	ka	CL	V	Imax	IC50	kout	$\sigma_{PK_PROP} \frac{2}{2}$	σ_{PD_PROP}	
Individual PK	43.2	24.5	30.4				44.8		
Individual PK/PD	48.7	17.4	21.0	7.2	96.9	12.3	31.7	42.6	

* In all cases Exchange algorithm (Ogungbenro, 2006, Computer Method Prog Biomed) with 0.01 step size was used

Optimal design for individual human TGFb inhibitor model

- PK
 - Two early samples with last time at upper bound 24h (due to proportional error model)
 - reasonable CVSE on structural parameters (ka 43%); slightly larger on proportional error (45%);
- PK/PD:
 - Repetition of all three sampling times;
 - Parameter CVSEs close to or <40 with exception of IC50 (97%)

Assessing clinically relevant designs

A number of different designs were considered

	Practical designs	Efficiency [%]	
<	<u>[0 1 3 6 8 16 24]</u>	90.5	\triangleright
	[0 2 6 8 16 24]	79.9	
	[0 1 3 6 12 24]	80.9	

Ka	CL	V	Imax	IC50	kout	$\sigma^2_{PK_PROP}$	$\sigma^2_{PD_{PROP}}$	
56.8	14.2	18.4	5.6	118.7	16.0	29.3	39.4	
60.5	16.9	22.2	6.30	121.6	16.22	31.65	42.57	
57.5	15.11	19.28	5.98	127.6	16.22	31.65	42.58	

A variant of the first design is currently being implemented in the clinic

Challenges in optimal design

Methodology

- Responses measured on very different time scales (clinical outcome scales in Alzheimer's disease)
 - TGFb study designed as if PK and p-SMAD inhibition measured on the same time scale (0-24h); more realistic different time frames
- sequential vs simultaneous design
- Theorethical proof/disproof of Equivalence theorem in multirespose models

Prospective rather than retrospective applications!

Back up slides

RAT observed versus individual predicted concentrations





Mouse PD profiles



Time (h)

Multivariate response design for an individual

$$y_{mj} = f_m(\theta, t_j) + \mathcal{E}_{mj}$$

$$\Sigma = \begin{pmatrix} \tau_{11} & \tau_{12} & \cdots & \tau_{1M} \\ \tau_{21} & \tau_{22} & \cdots & \tau_{2M} \\ \cdots & \cdots & \cdots & \cdots \\ \tau_{M1} & \tau_{M2} & \cdots & \tau_{MM} \end{pmatrix} = \{\tau_{qm}\}_{1 \le q, m \le M} \qquad F(\theta, \xi) = \sum_{q=1}^{M} \sum_{m=1}^{M} \left[\frac{\partial f_q(\theta, \xi)}{\partial \theta} \right] \tau^{qm} \left[\frac{\partial f_m(\theta, \xi)}{\partial \theta} \right]^T$$

$$\frac{\partial f_m(\theta,\xi)}{\partial \theta} = J_m(\theta,\xi) = \begin{bmatrix} \frac{\partial f_m(\theta,t_1)}{\partial \theta_1} \cdot \frac{1}{\sqrt{(\sigma_{m1}^2 + \sigma_{m2}^2 f_m(\theta,t_1)^2)}} \end{bmatrix} \cdot \cdot \begin{bmatrix} \frac{\partial f_m(\theta,t_n)}{\partial \theta_1} \cdot \frac{1}{\sqrt{(\sigma_{m1}^2 + \sigma_{m2}^2 f_m(\theta,t_n)^2)}} \end{bmatrix} \\ \cdot \cdot \begin{bmatrix} \frac{\partial f_m(\theta,t_1)}{\partial \theta_p} \cdot \frac{1}{\sqrt{(\sigma_{m1}^2 + \sigma_{m2}^2 f_m(\theta,t_1)^2)}} \end{bmatrix} \cdot \cdot \begin{bmatrix} \frac{\partial f_m(\theta,t_n)}{\partial \theta_p} \cdot \frac{1}{\sqrt{(\sigma_{m1}^2 + \sigma_{m2}^2 f_m(\theta,t_n)^2)}} \end{bmatrix} \end{bmatrix}$$

$$\frac{\partial f_m(\theta,\xi)}{\partial \theta} = J_m(\theta,\xi) = \left\{ \frac{\partial f_m(\theta,t_j)}{\partial \theta_k} \cdot \frac{1}{\sqrt{(\sigma_{m1}^2 + \sigma_{m2}^2 f(\theta,t_j)^2)}} \right\}_{\substack{1 \le j \le n \\ 1 \le k \le p \\ 1 \le m \le M}}$$

Population multivariate response design

$$\begin{aligned} y_{imj} &= f_m(\theta_i, t_{ij}) + \varepsilon_{imj} \\ y_{21} & y_{22} & \cdots & y_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ y_{n1} & y_{n1} & \cdots & y_{nM} \end{aligned} \right| y_i = \operatorname{vec}(Y_i) = [y_{i1}^{'}, y_{i2}^{'}, \dots, y_{iM}^{'}] \\ \varepsilon_i = \operatorname{vec}(\Gamma_i) = [\eta_{i1}^{'}, \varepsilon_{i2}^{'}, \dots, \varepsilon_{iM}^{'}] \\ \varepsilon_i = \operatorname{vec}(\Gamma_i) = [\eta_{i1}^{'}, \varepsilon_{i2}^{'}, \dots, \varepsilon_{iM}^{'}] \\ R = \begin{bmatrix} R_{11} & R_{12} & \cdots & R_{1M} \\ R_{21} & R_{22} & \cdots & R_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ R_{n1} & R_{n2} & \cdots & R_{nM} \end{bmatrix} \\ R_{qm}(j,l)\Big|_{j=l} = \left\{ \tau_{qm} \sqrt{\left(\sigma_{q1}^2 + \left(\sigma_{q2}^2 * f_q(\theta, t_j)^2\right)\right) * \left(\sigma_{m1}^2 + \left(\sigma_{m2}^2 * f_m(\theta, t_j)^2\right)\right)} \right\}_{\substack{l \le q, m \le M} \\ I \le j, l \le n} \\ R_{qm}(j,l)\Big|_{j\neq l} = \{0\}_{\substack{l \le q, m \le M} \\ I \le j, l \le n} \\ \lambda = [\omega_1^2, \dots, \omega_p^2, \sigma_{11}^2, \dots, \sigma_{1M}^2, \sigma_{21}^2, \dots, \sigma_{2M}^2] \\ F(\Psi, \xi_i) = \left[-\frac{\partial^2 l(\Psi, y_i)}{\partial \Psi^T \partial \Psi} \right] \\ y_{im} = f_m(\theta, b_i, \xi_i) + \varepsilon_{im} \cong f_m(\theta, 0, \xi_i) + \frac{\partial f_m^T(\theta, b_i, \xi_i)}{\partial b_i}\Big|_{b_i = 0} b_i + \varepsilon_{im} \end{aligned}$$

$$F(\Psi,\xi_i)_{ab} = \left\{ J_a^T V^{-1} J_b + \frac{1}{2} tr \left(\frac{\partial V}{\partial \Psi_a} V^{-1} \frac{\partial V}{\partial \Psi_b} V^{-1} \right) \right\}_{1 \le a,b \le (p^{*}2 + 2^{*}M)}$$

Predicted and observed tumor growth delay

