
**Modelling a complex input process in a
population pharmacokinetic analysis:
*example of mavoglurant oral absorption in
healthy subjects***

Thierry Wendling

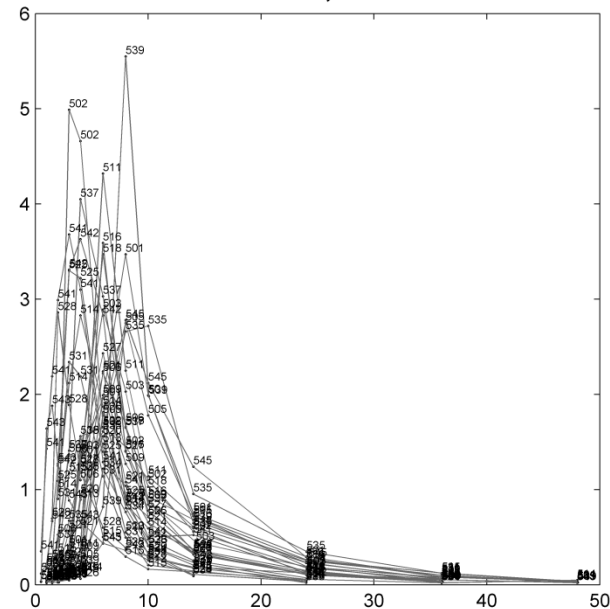
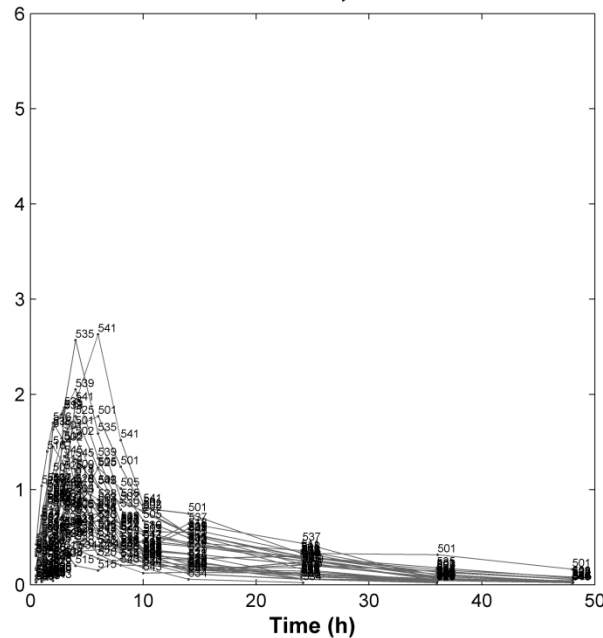
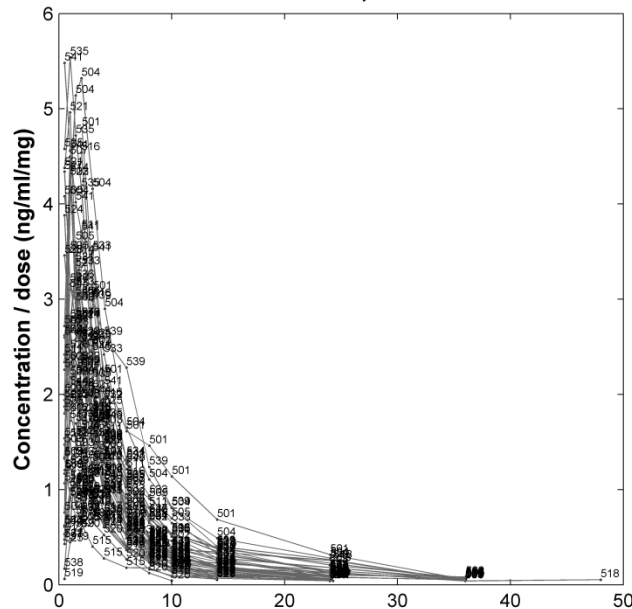
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Mavoglurant

- **Mavoglurant (MVG)** is a structurally novel **antagonist at the metabotropic glutamate receptor 5**, currently under clinical development at Novartis Pharma AG for the treatment of CNS diseases.
- An **oral immediate-release (IR) formulation** was initially used in the Phase I clinical studies:
 - Most of the **adverse events** (*e.g.* dizziness, fatigue, hallucination *etc.*) were related to **peak plasma concentrations**
- An **oral modified-release (MR) formulation** was developed in order to **reduce peak concentrations** without substantial change in the systemic exposure.
- The **pharmacokinetics (PK)** of the IR and MR formulations were compared in a cross-over study in healthy subjects (Study A2167, n=44).
- Since MVG is considered as a **BDDCS class II** compound, **food effect** was also investigated for the MR formulation.
- The PK of MVG following a brief **intravenous (IV) infusion** (10 min) was also evaluated in another study in healthy volunteers (Study A2121, n=120).

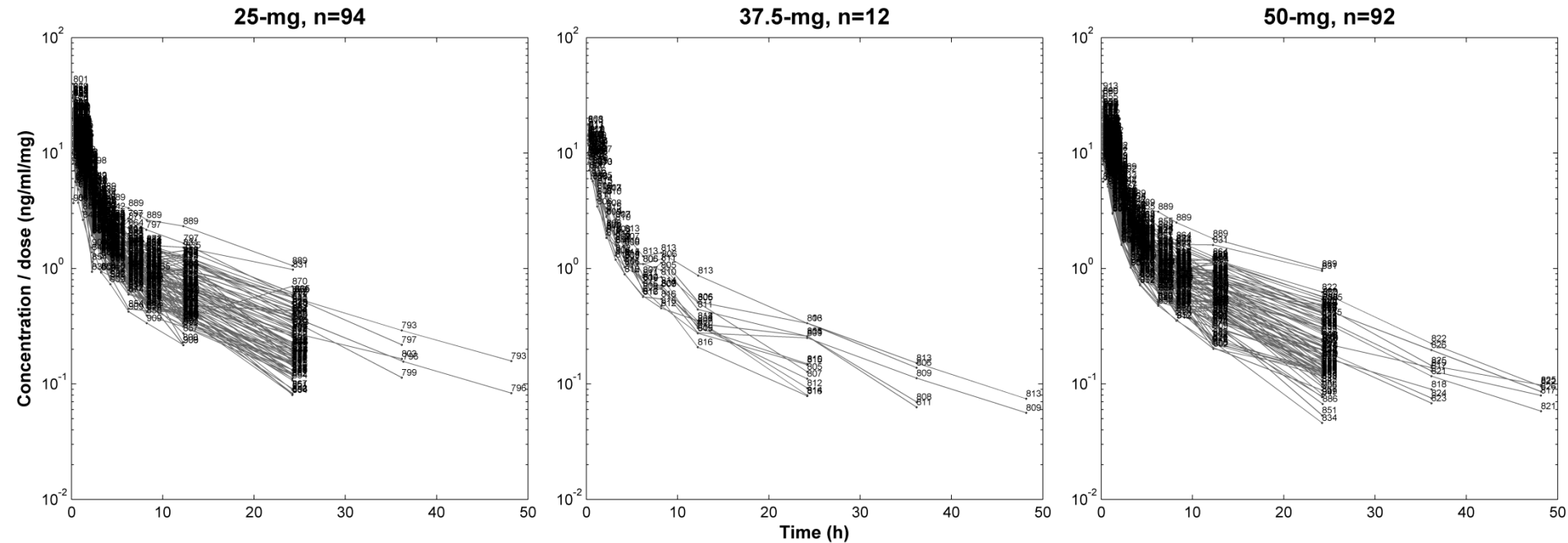
Oral administration ; cross-over design



- ## ➤ Food effect on the MR formulation's PK

Plasma concentration-time profiles

IV administration



- Bi-exponential decrease
- No sign of non-linearity with dose

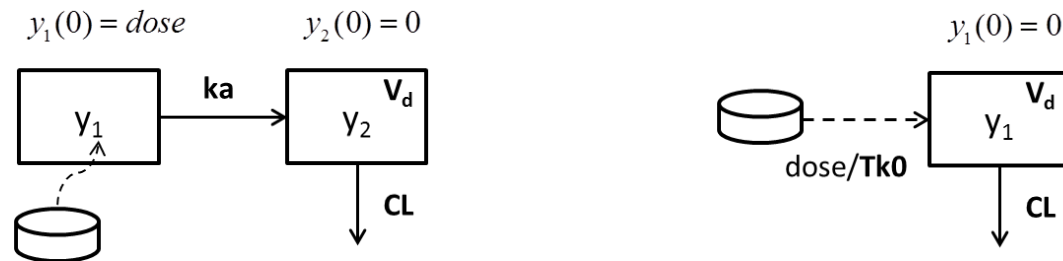
Motivation for a population PK analysis

- Describe **MVG disposition** in the population and identify any contributing **demographic covariates**.
- Compare the **input characteristics** (rate and extent) of the IR and MR formulation.
- Quantify the **effect of a high fat meal** on the bioavailability and input rate of the MR formulation.
- Predict the impact of MVG release-rate and of food intake on the **steady-state concentration range** provided by a twice-daily repeated administration of the oral formulations.

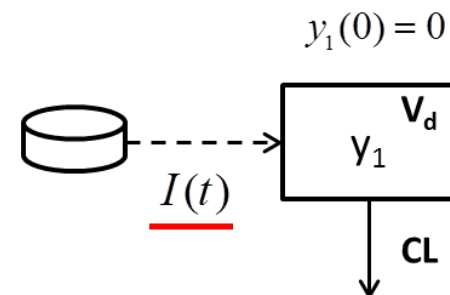
Adequate input model !

Modelling complex extravascular PK profiles

- **Conventional models** that assume a **first-order** or **zero-order** input rate for a fixed period are inadequate to model complex concentration-time profiles:



- Development of a more **mechanistic model** (incorporating drug dissolution, absorption, gut-wall metabolism *etc.*) can be time consuming and is challenging when only little **drug-** and **formulation-specific prior information** is available.
- Alternatively, a **flexible empirical function** can be used to model the **rate of input** into the system:
 - Polynomial (*Cutler, 1978*)
 - Cubic spline (*Fattinger and Verrota, 1995*)
 - Gamma distribution (*Weiss, 1983*)
 - Weibull distribution (*Bresolle et al, 1994*)
 - **Inverse Gaussian distribution (*Weiss, 1996*)**
 - *Etc.*



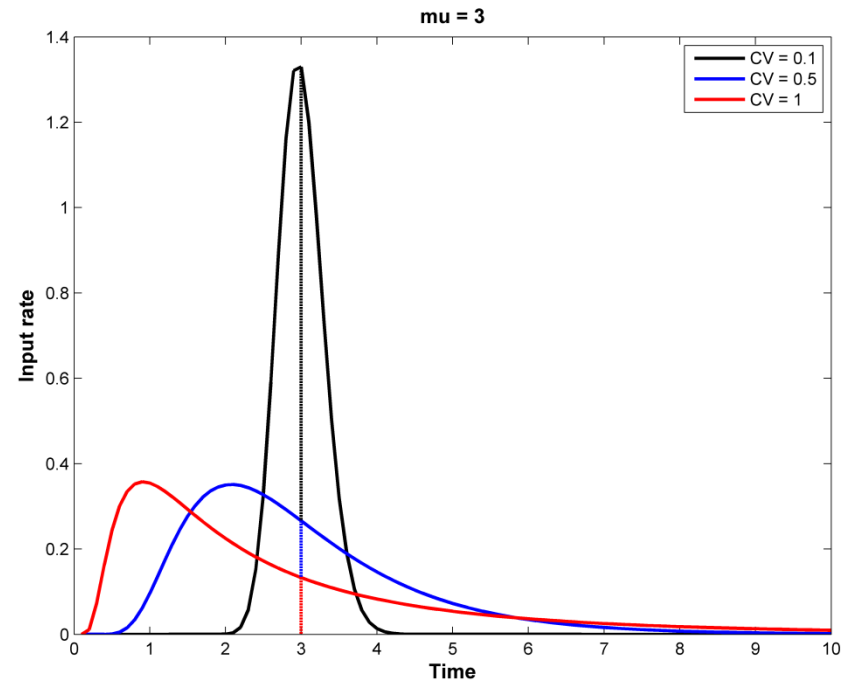
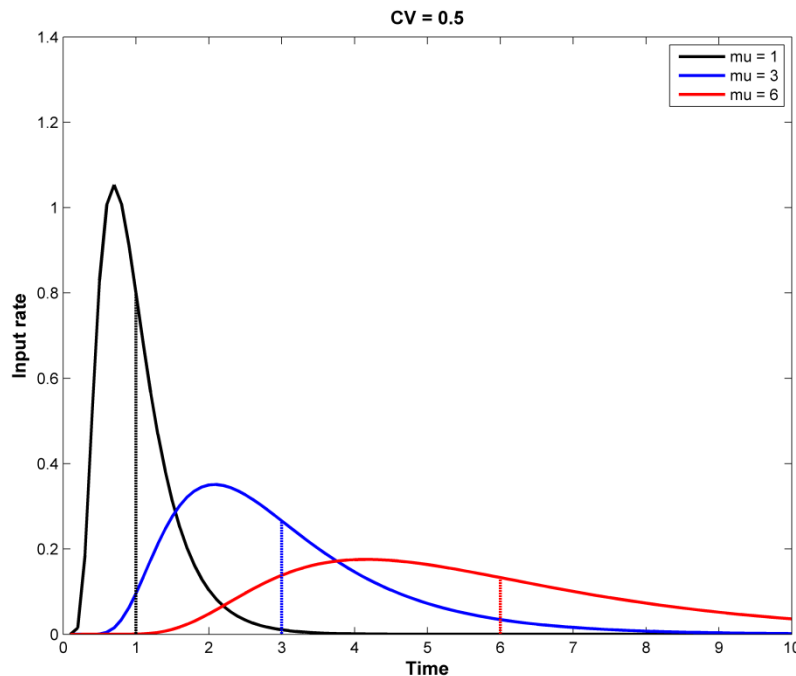
Inverse Gaussian (IG) distribution

Density function

$$IG(t) = \sqrt{\frac{\mu}{2\pi CV^2 t^3}} \times \exp\left[-\frac{(t - \mu)^2}{2CV^2 \mu \cdot t}\right]$$

Two parameters:

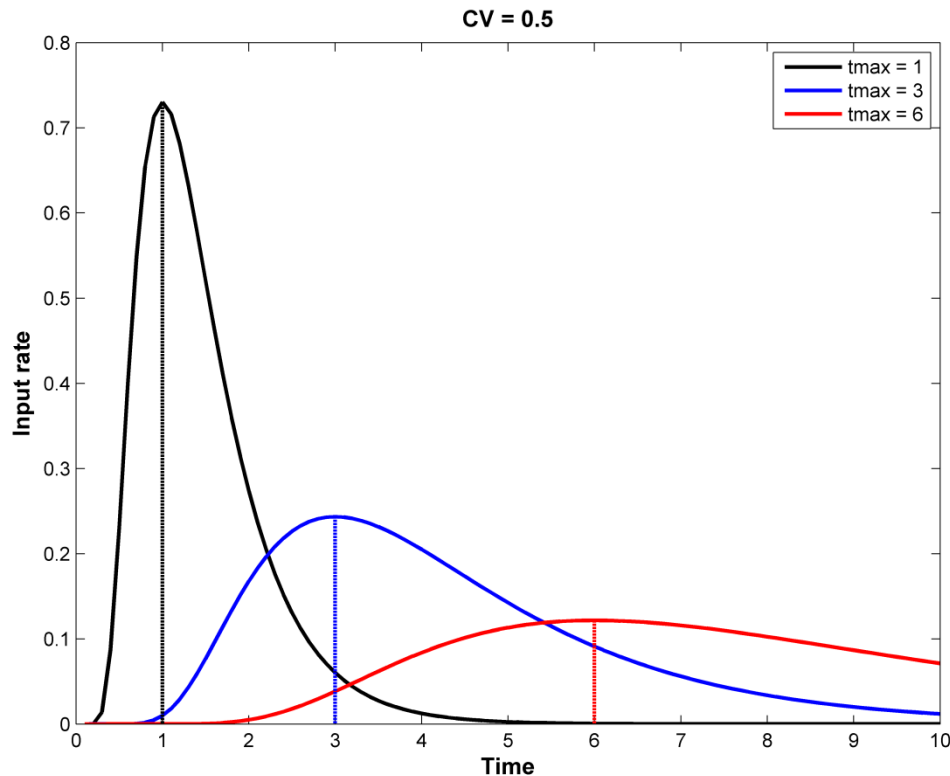
- The mean of the distribution μ
- The relative dispersion of the mean CV (skewness)



- When **CV tends to 0**, the IG distribution becomes a **Normal distribution** (symmetrical)
- More flexible than the log-normal distribution (*Chhikara and Folks, 1977*)

IG distribution

Mode



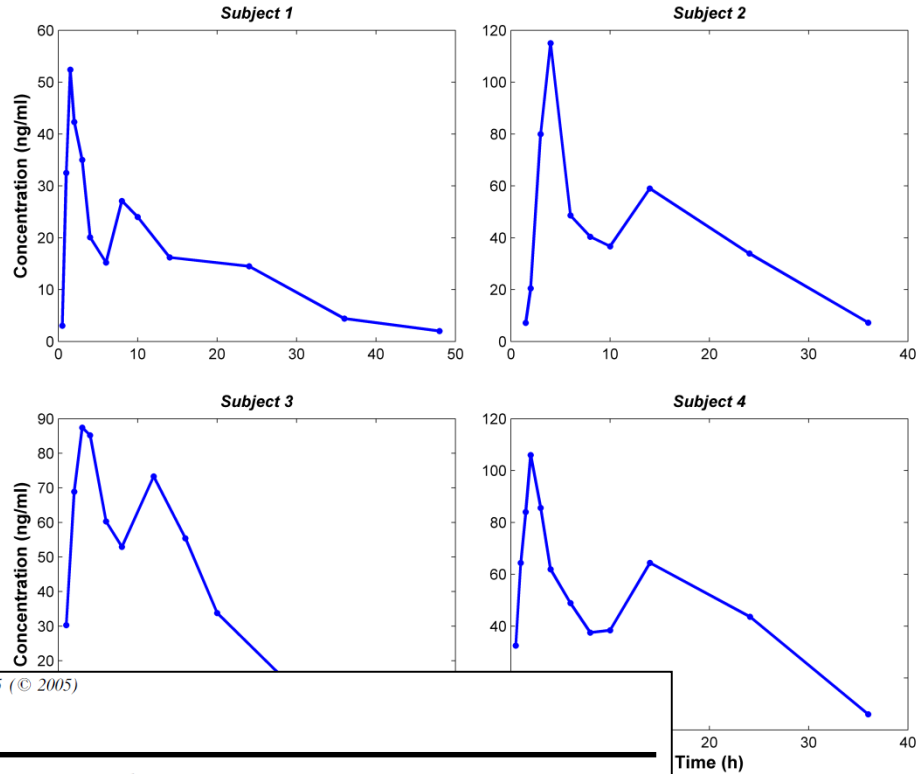
$$tmax = \mu \times \left[\sqrt{1 + \frac{9}{4} CV^4} - \frac{3}{2} CV^2 \right]$$

The mode is more informative: time at which the **input rate** reaches its **maximum**

- Convenient for initial parameter values
- Easier interpretation of results

How to capture multiple-peak profiles?

- The input func
- This can easily functions that mode (avoid fl



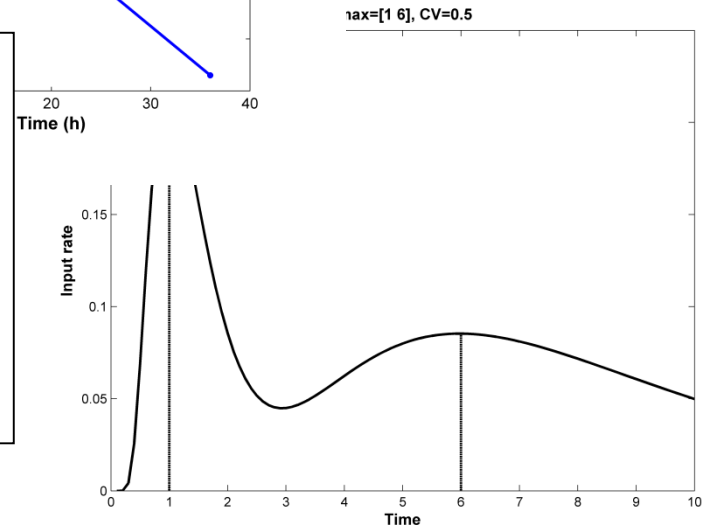
Pharmaceutical Research, Vol. 22, No. 8, August 2005 (© 2005)
DOI: 10.1007/s11095-005-5266-8

Research Paper

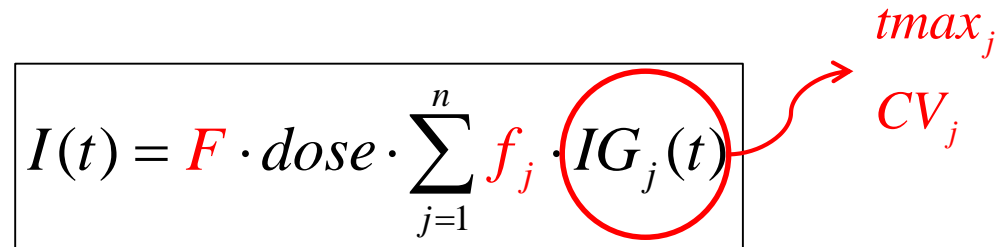
The Use of a Sum of Inverse Gaussian Functions to Describe the Absorption Profile of Drugs Exhibiting Complex Absorption

Chantal Csajka,¹ David Drover,² and Davide Verotta^{1,3,4}

Received December 1, 2004; accepted March 23, 2005



A weighted sum of n IG functions as an input rate function

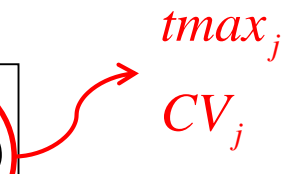
$$I(t) = F \cdot dose \cdot \sum_{j=1}^n f_j \cdot IG_j(t)$$


- The **absolute bioavailability** F can be directly estimated if IV data are available.
- The parameters f_j are the **weights** for the IG functions (fraction of bioavailable-dose) such that:

$$\sum_{j=1}^n f_j = 1$$

- The number of structural parameters is $n \times 3$:
 - $F, f_j, tmax_j, CV_j$ for $j=1, \dots, n$
 - f_n is derived from the f_j ($j=1, \dots, n-1$) rather than estimated, to constrain the sum

Stochastic model for a sum of IG functions as input function

$$I(t) = F \cdot dose \cdot \sum_{j=1}^n f_j \cdot IG_j(t)$$


The diagram shows the equation $I(t) = F \cdot dose \cdot \sum_{j=1}^n f_j \cdot IG_j(t)$ enclosed in a black rectangular box. A red circle is drawn around the term $IG_j(t)$. A red arrow originates from the right side of this circle and points towards the text $tmax_j$ and CV_j , which are written in red and stacked vertically to the right of the box.

- Using a sum of IG functions as an input function, one approach to build the statistical model is to **assign a random-effect on each parameter of each IG function** (*Csajka et al, 2005*), and assess the parameter estimates and precisions (deterministic identifiability).
- However, it is more “reasonable” to estimate the same variance for the random-effects of the n ***tmax***, as well as for those of the n ***CV*** (e.g. option “SAME” in NONMEM®)
 - The number of parameters is reduced (more numerically stable)
 - The cost is a decrease in flexibility
- **Bootstrapping** can be applied to check that the estimated variance of a random-effect is statistically significantly different from zero and has a reasonable precision.

Constraining the subject-specific input parameters

- To ensure that the **IG densities** are **naturally ordered** (important for structural identifiability), the constraint $tmax_{j,i} \geq tmax_{j-1,i}$ was imposed as follows:

$$tmax_{j,i} = tmax_{j-1,i} + \theta_{tmax_j} \cdot e^{\eta_{tmax_j,i}}, \text{ for the } i^{th} \text{ subject and for } j=2,..,n$$

- To be **consistent with physiology**, the constraint $0 \leq F_i \leq 1$ was imposed by defining F as **logit-normally distributed** within the population.
- Constraining the **joint distribution** of the f_j parameters such that:

$$\sum_{j=1}^n f_{j,i} = 1$$

while ensuring that $0 \leq f_{j,i} \leq 1$ (for $j=1,...,n$), can be performed by use of a **multivariate logistic-normal distribution** (Tsamandouras et al, 2014; in manuscript).

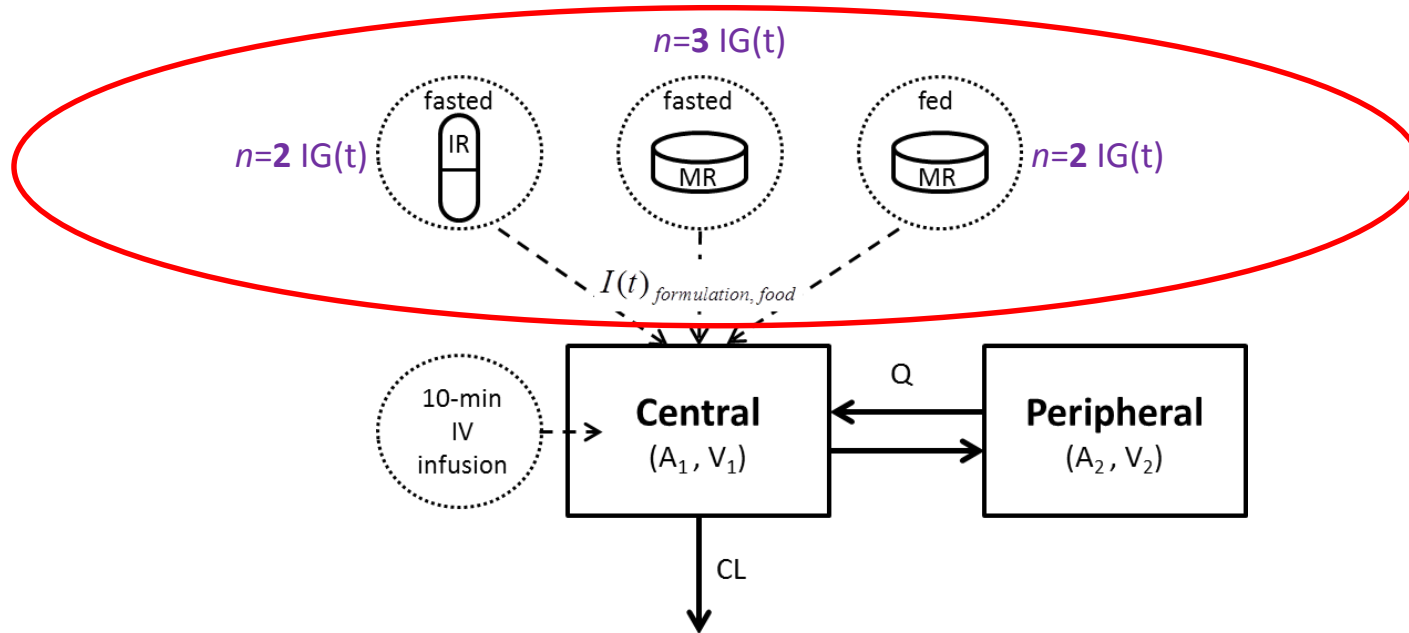
Impact of formulation and food intake on MVG input kinetics

- It was obvious from the raw data that MVG **input properties** depend on the **formulation** and **food conditions** at drug administration.
- Therefore, the **input rate function** was estimated **specifically for each formulation-food condition** rather than testing these factors as categorical covariates for the input parameters.
- **Each subset of data** was first analysed **together with IV data** to determine the **optimal number of IG terms** for each input function.
- Subsequently, all data were pooled and analysed using NONMEM®.
- The model was implemented as a system of two ODEs:

$$\begin{aligned}\frac{dA_1}{dt} &= I_{\text{formulation, food}}(t) - A_1 \cdot (k_{10} + k_{12}) + A_2 \cdot k_{21} \\ \frac{dA_2}{dt} &= A_1 \cdot k_{12} - A_2 \cdot k_{21}\end{aligned}$$

Structure of MVG population PK model

Oral route



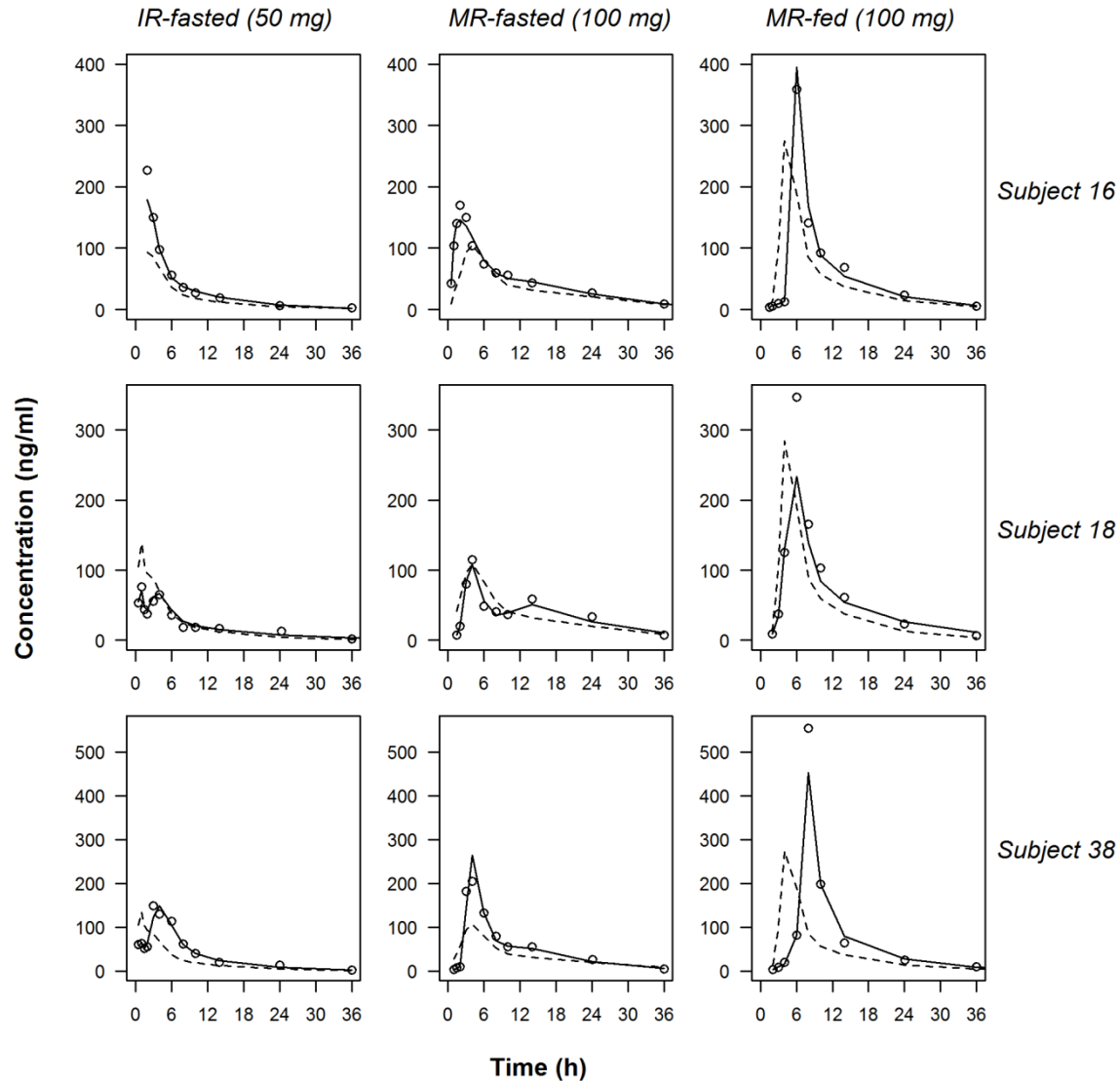
- The **volume terms** are functions a of subject's **bodyweight (BW)**:

$$V_{k,i} = \theta_{V_k} \left(\frac{BW_i}{BW_{med}} \right)^{\theta_{BW,V_k}} \cdot e^{\left(\eta_{V_k,i} \right)}$$

for $k=1,2$ and the i^{th} individual

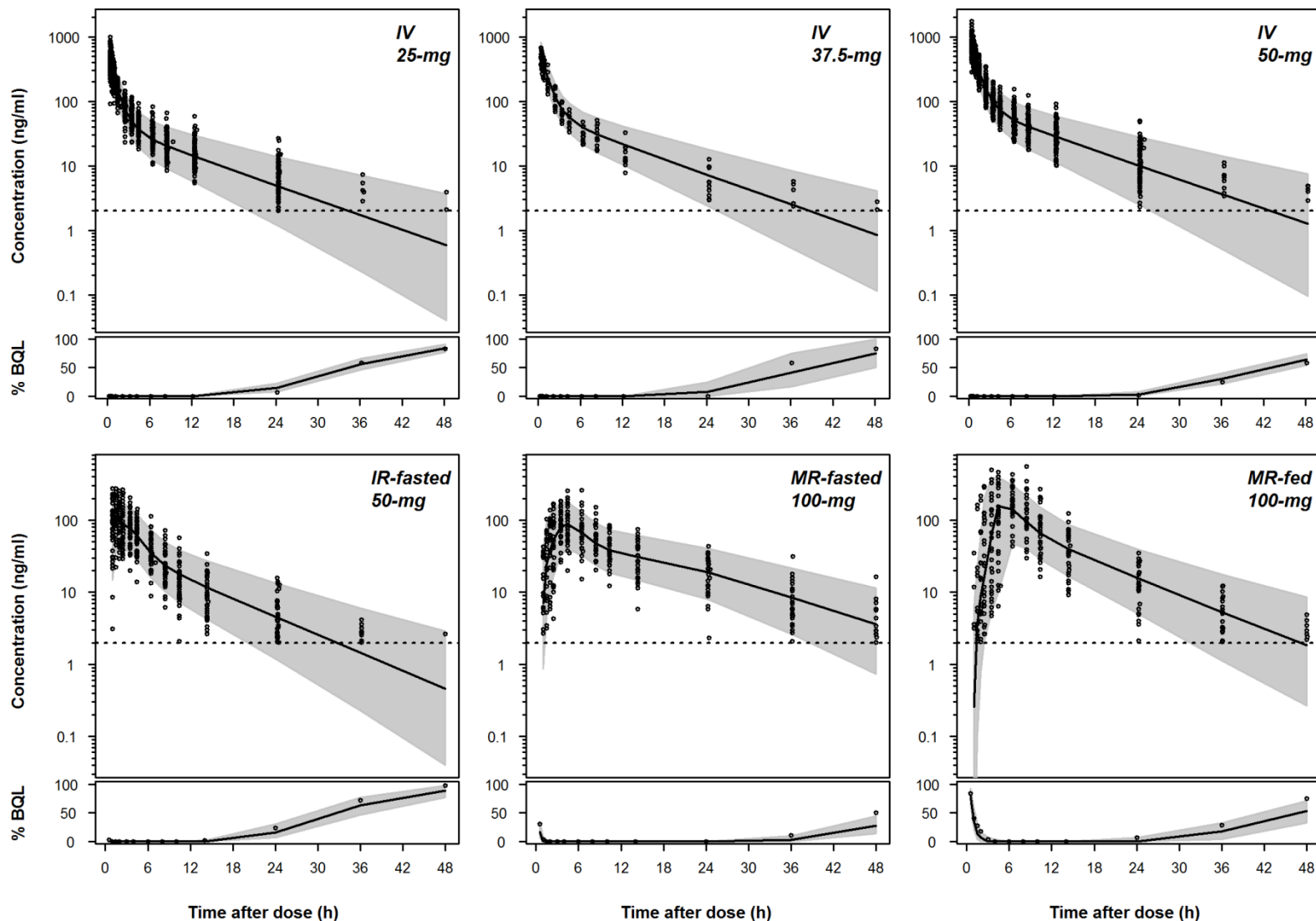
Goodness-of-fit

- Observed concentrations — Individual predictions - - Population predictions



Visual predictive check of the model

○ Observed concentrations ■ 90% prediction interval — Median of the predicted concentrations



Application of the input model

Simulation of the time course of the input rate and F

- The **derived input functions** $I_{\text{formulation,food}}(t)$ can be used directly to simulate the **time course of the input rate** for each formulation-food condition.
- The **time course of the bioavailability** can be simulated using the following function :

$$F_A(t) = F \cdot \sum_{j=1}^n f_j \cdot IGcdf_j(t) \quad \text{with} \quad F_{A,t \rightarrow \infty}(t) = F$$

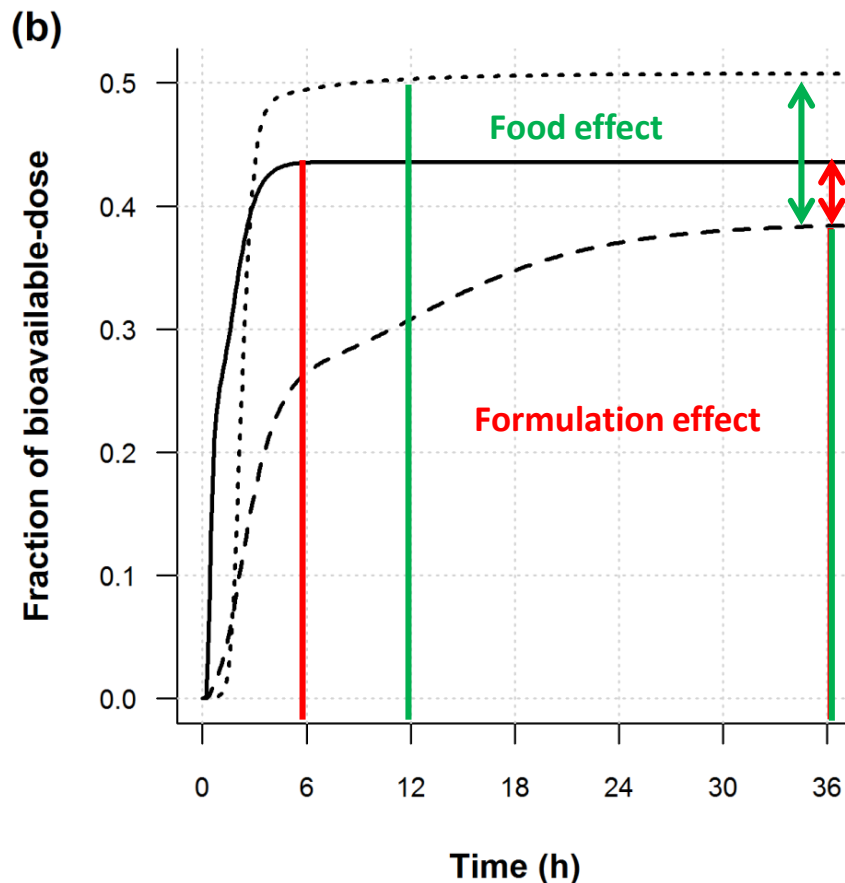
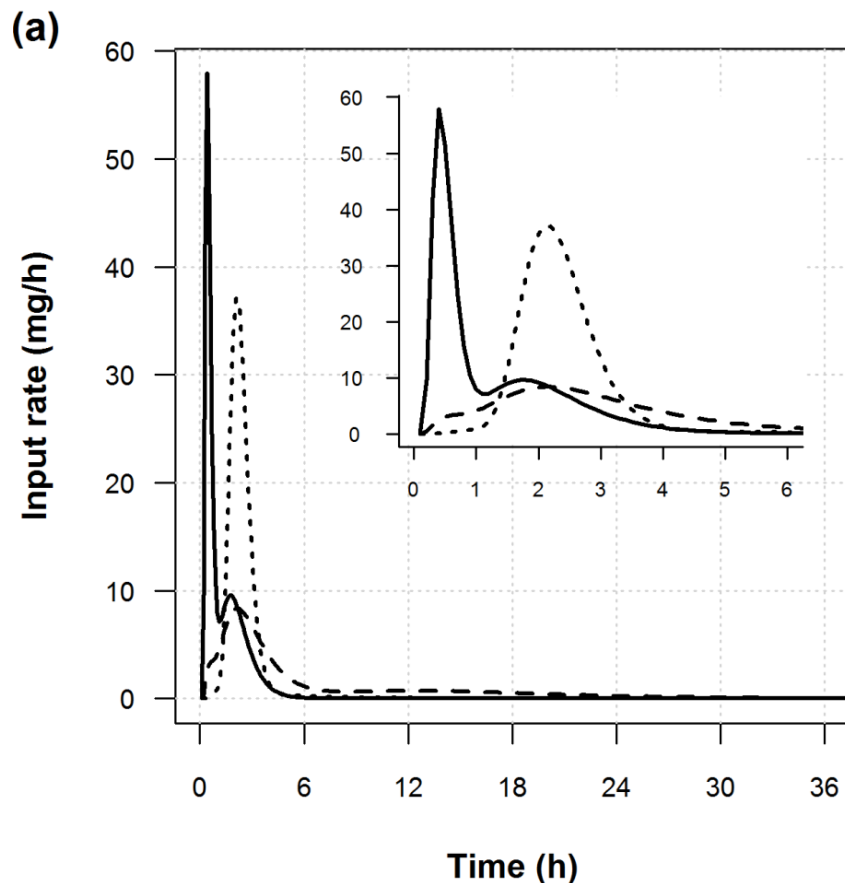
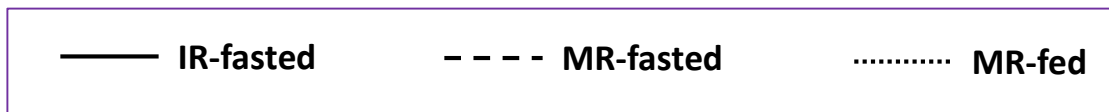
where $IGcdf_j(t)$ is the j^{th} IG cumulative distribution function (cdf).

- The **IG cdf** can be called in the software R for instance (*pinvgauss*) but is parameterized in terms of μ and λ :

$$\mu = tmax / \left[\sqrt{1 + \frac{9}{4} CV^4} - \frac{3}{2} CV^2 \right] \quad \text{and} \quad \lambda = \frac{\mu}{CV^2}$$

Input rate / bioavailability *versus* time profiles

Standard individual in the population

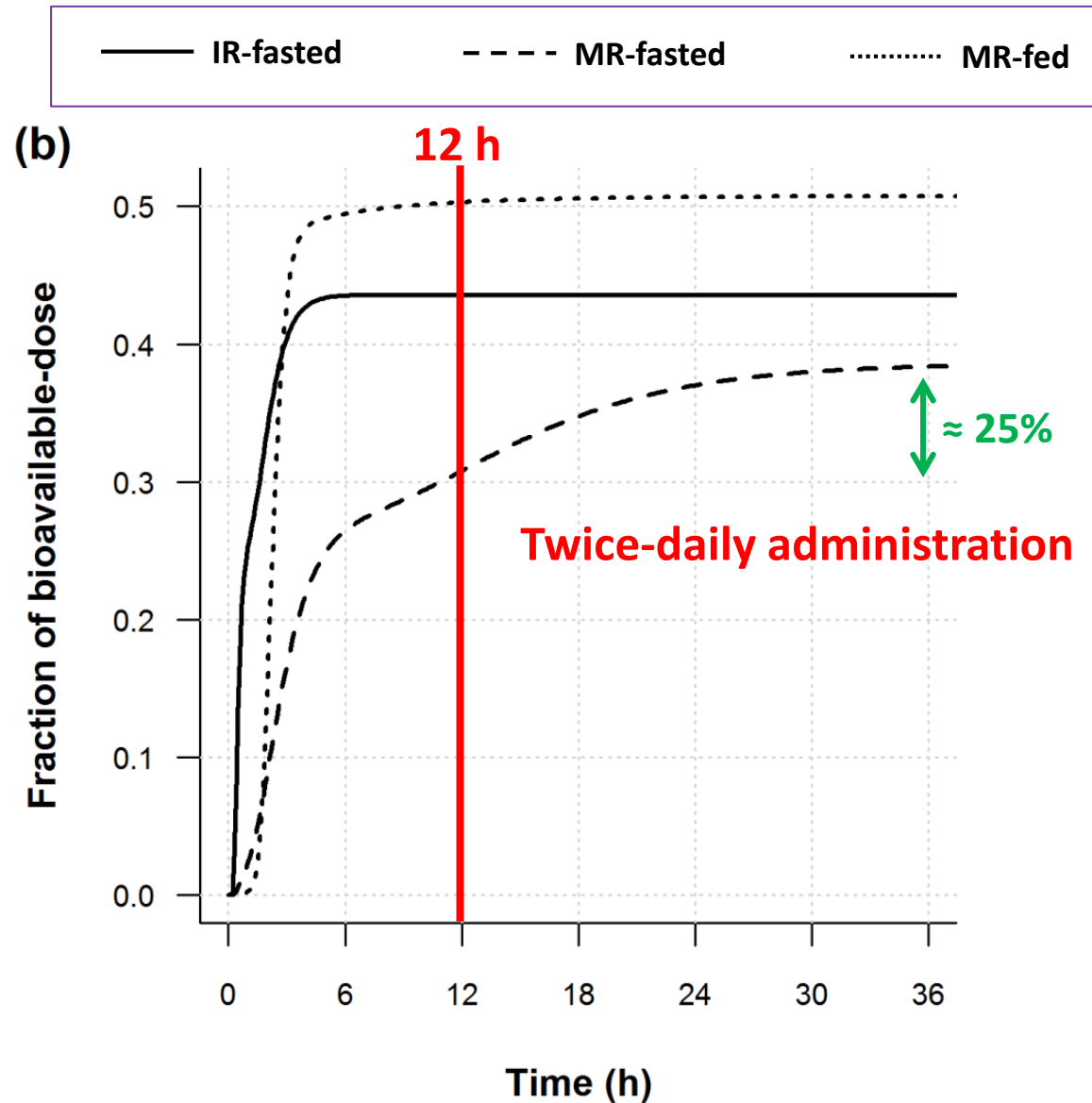


Using an empirical input model for multiple doses

- To eliminate the assumption that a dose has been completely absorbed prior to the next dosing event, **dose superimposition** should be implemented when using the **analytical solution** of the input model for a **repeated dose design**.
- Using NONMEM®, dose superposition can be implemented in a **user-defined FORTRAN subroutine**.
- The method was adapted to the use of a **sum of IG functions** as input function.

J Pharmacokinet Pharmacodyn (2012) 39:251–262 DOI 10.1007/s10928-012-9247-3	$I(t) = F \cdot dose \cdot \sum_{j=1}^n f_j \cdot IG_j(t)$	
ORIGINAL PAPER		
Implementation of dose superimposition to introduce multiple doses for a mathematical absorption model (transit compartment model)		
Jun Shen · Alison Boeckmann · Andrew Vick		
Received: 5 January 2012 / Accepted: 1 March 2012 / Published online: 4 May 2012 © Springer Science+Business Media, LLC 2012		

Does dose superimposition need to be implemented?

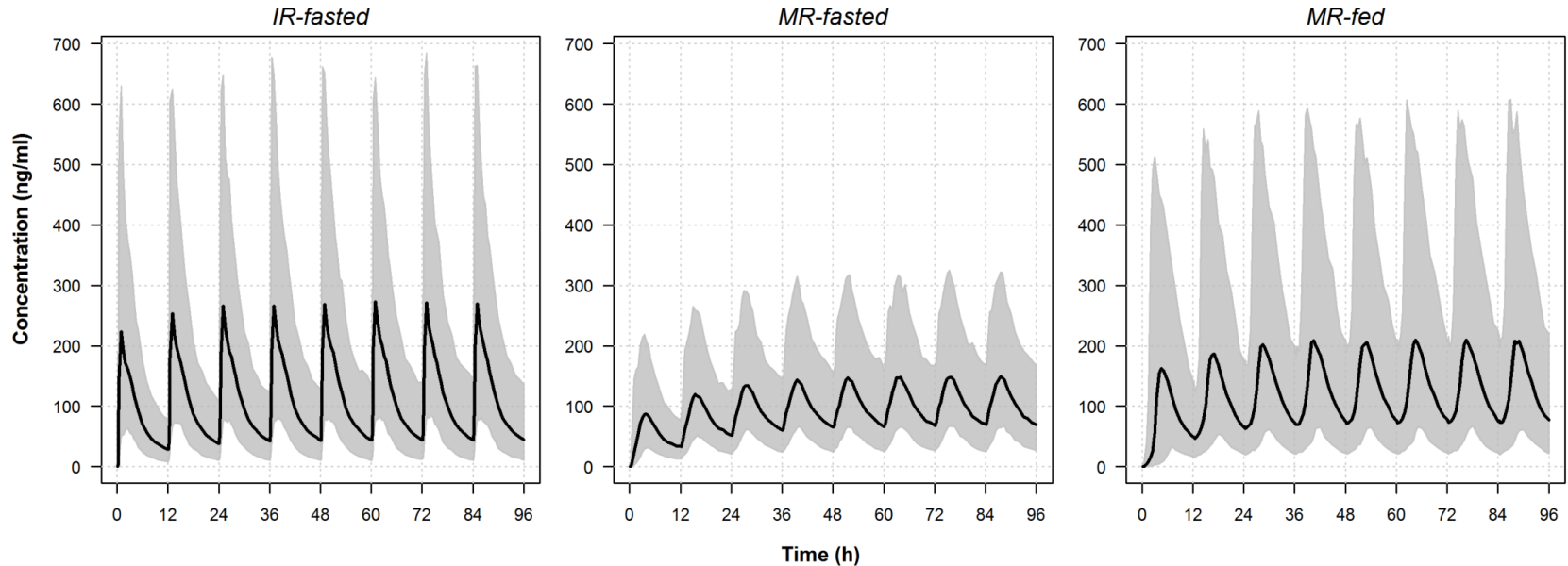


Application of the PK model

Simulation of the steady-state concentration range

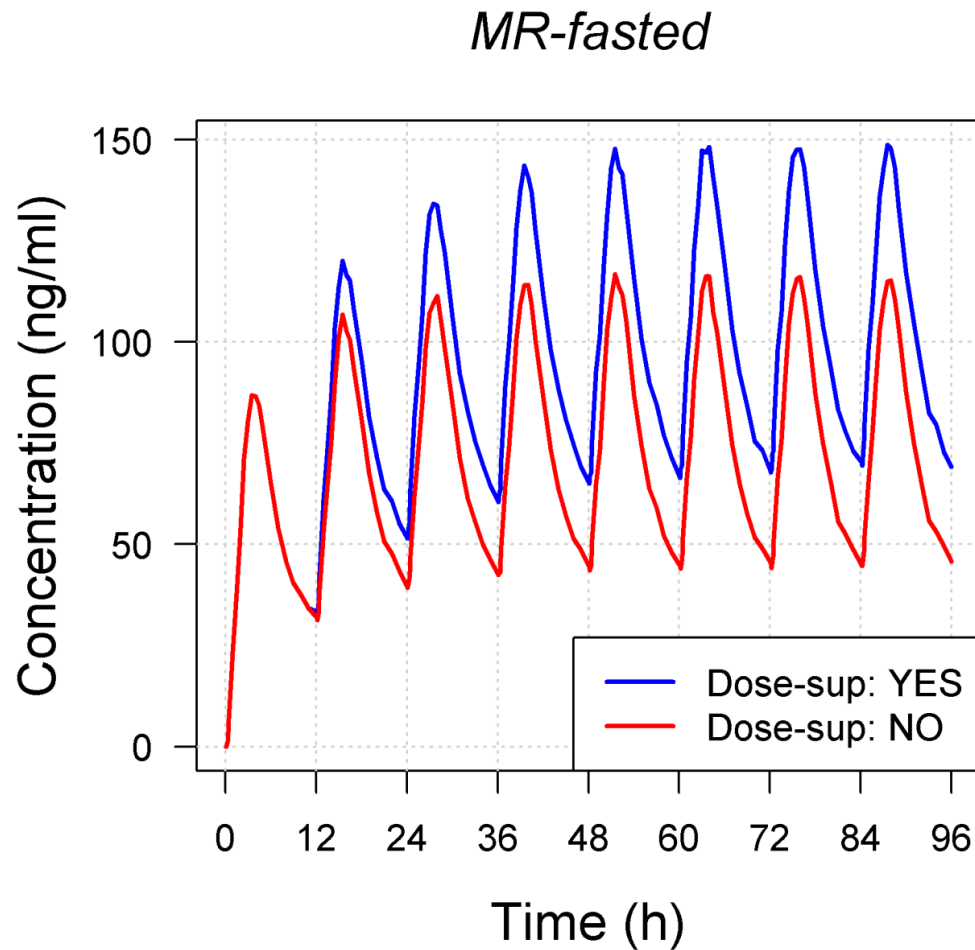
100-mg twice daily

■ 95% prediction interval — Median of the predicted concentrations



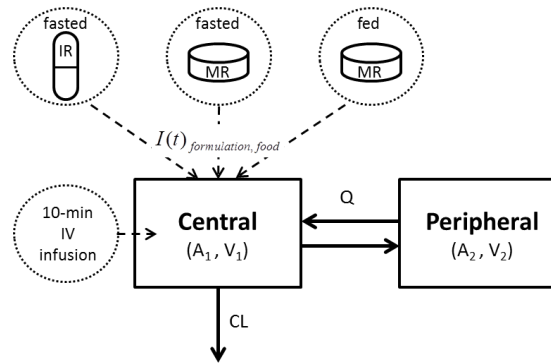
- The MR formulation provides a **slightly lower steady-state concentration range** than the IR formulation, with **lower peaks** (possibly better drug tolerance).
- The **steady-state exposure** to MVG strongly depends on the **food state** at each administration of the MR formulation.

Neglecting dose superimposition



The difference depends on the duration of the input process !

Conclusions on MVG population PK model



- **Advantages:**

- **Easy implementation** and **fast** analysis runs
- **Disposition model mechanistic enough** to evaluate the impact of covariates (*e.g.* demographics)
- **Very flexible input model** that can capture complex profiles with multiple peaks
- Although empirical, the derived input function helps to gain **insight into the input process** (*e.g.* comparison of the time course of bioavailability between formulations)

- **Disadvantages :**

- **Can't extrapolate beyond the studied population and experimental conditions** (*e.g.* other disease states or age/weight range) due to its descriptive/empirical nature
- Doesn't provide much information about the **absorption process** itself and the **first-pass effect**
- Predicting concentrations in **clinically relevant tissues** is not possible (*i.e.* target sites and tissues exposed to drug toxicity)

Perspectives

- Develop a **physiologically-based PK model** for MVG in order to:
 - Gain insight into the underlying mechanisms of absorption, distribution and elimination
 - Predict concentrations in clinically relevant tissues (*e.g.* brain)
 - Extrapolate outside the studied population such as in a paediatric population
- Reduce the model using **proper lumping** technics and keeping clinically relevant tissues in the model (*Dokoumetzidis and Aarons, 2009*).
- Optimise the model based on clinical data using a **Bayesian approach** (*Gueorguieva et al, 2006*)
 - Integrate the preclinical knowledge
 - Circumvent structural identifiability issues

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Back up

Model-Based Evaluation of the Impact of Formulation and Food Intake on the Complex Oral Absorption of Mavoglurant in Healthy Subjects

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Flexibility of the input model

9/1000 simulated profiles

MR-fasted

