# qPnoMAD: A Residual-Trend-Based, ML-Guided Tool for Automated PopPK Model Development

Undine Falkenhagen<sup>1</sup> Zrinka Duvnjak<sup>2,3</sup> H. Maxime Lagraauw<sup>1</sup> Robin Michelet<sup>1</sup> Lars Lindbom<sup>1</sup>

<sup>2</sup>Freie Universität Berlin, Berlin, Germany <sup>1</sup>qPharmetra LLC <sup>3</sup>PharMetrX, Berlin, Germany

#### qP's nonlinear mixed-effects Model Automated Developer

- PopPK model development is traditionally iterative and subjective, but based on quantifiable heuristics
- Machine learning can be used to automate decision-making in model building
- Trends in residuals can point towards plausible next modelling steps

#### Overall model building strategy

- 1 Initialize with simple model: first-order elimination, IIV on CL
- Select next component using Random Forest (RF) classifier
- Estimate new model using NONMEM
- **Evaluate improvement** based on statistically significant  $\triangle \mathsf{OFV}$
- 5 Repeat from step 2 until no further significant improvements

## Random Forest Classifier guides next component proposal based on features

#### Inputs:

- Training data (features from simulated data) with known true model)
- State (current model structure)
- Possible next states (candidate component, e.g. 2nd CMT or IIV)
- Test data (features of current model)

#### **Process:**

For each candidate component per modelling step:

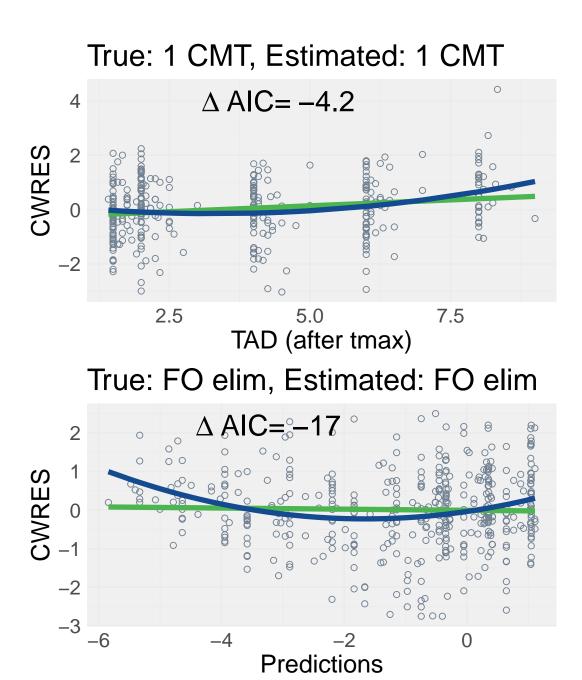
- 1 Filter training data: retain rows with structurally compatible components to the current estimated state (e.g., same elimination structure when testing elimination)
- Train a Random Forest (1000 trees, max depth 10, fixed seed) using selected features
- Predict probability for each component

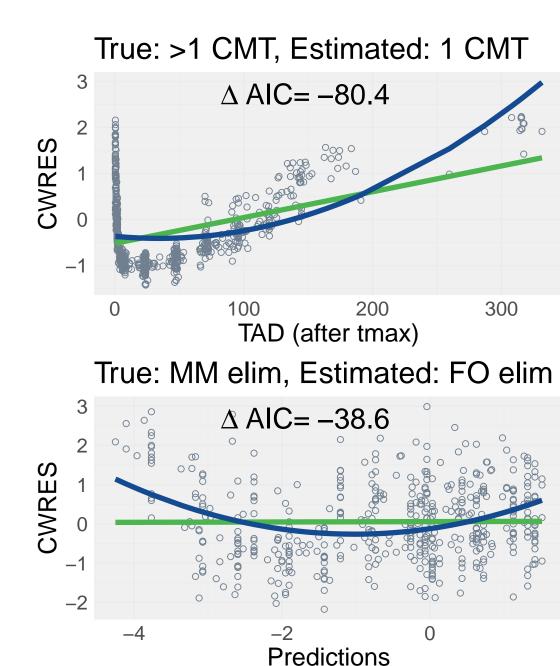
#### Output:

Proposed component to turn on/off next

#### Features used for the classifier:

- AIC difference between a linear and a quadratic relationship between:
  - lacksquare CWRES vs. TAD prior to  $t_{max}$  lacksquare CWRES vs. TAD after  $t_{max}$ CWRES vs. PRED
- The sign of the second-order parameter (positive: ∨ , negative: ∧)
- For each IIV parameter: the p-value of a test of variance homogeneity (Fligner-Killeen) between the post-hoc ETAs and a reference distribution with 15% CV





#### **Example Feature means for filtered esti**mated and varying true models:

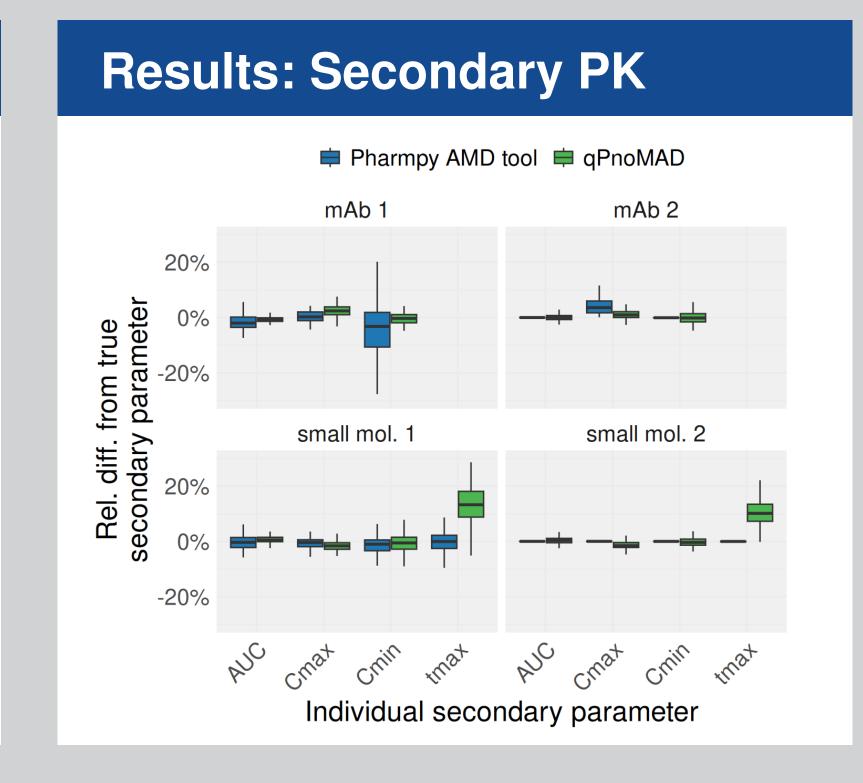
	True Elimination		True Compartments	
Feature	FO	MM	1	>1
$\triangle AIC_{TAD < tmax}$	-19	-2.4	-13	-24
$\triangle AIC_{TAD>tmax}$	-28	-39	-4.2	-82
$\triangle AIC_{PRED}$	-17	-39	-8.1	-44
sign <sub>TAD<tmax< sub=""></tmax<></sub>	-0.063	-0.11	-0.049	-0.11
sign <sub>TAD&gt;tmax</sub>	0.53	0.52	0.44	0.72
sign <sub>PRED</sub>	0.32	0.42	0.26	0.48

Estimated model: 1 compartment with FO elimination. True models: FO or MM elimination and 1 or 2-3 compartments. Feature means differ by true model, indicating discriminative value.

### **Evaluation on simulated data**

- Simulated (modified) base models from published drug development programs
  - Small molecule [1]
  - mAb [2]
- Simulated study designs (Phase I and II, SAD/MAD) align with true model studies
  - Small molecule: 143 IDs, 18-29 samples per ID
  - mAb: 100 IDs, 13-31 samples per ID
- qPnoMAD and Pharmpy AMD tool 1.6.0 [3] performance evaluated on all datasets

#### **Results: Modelling process** mAb 1 small mol. 1 small mol. 2 FO Abs Rate **ZO** Abs Rate Lag Time State 3-comp FO Elim on FO Abs Rate IIV **ZO Abs Rate IIV** Lag Time IIV |AOFV| CL IIV **→** 200 **→** 400 QIIV V2 IIV Q2 IIV V3 IIV **VMAX IIV** 1 3 5 11 12 18true 1 4 7 10 13 18 22 26 27true 1 5 9 14true Run number



#### Challenges > **Future work**

- Choice of Initial values
- Unstable runs (adding IIV may lead to higher OFV)
- Repeated checks of the same -> components Michaelis-Menten is slow and
- often evaluated early on
- True model is not necessarily → best (in terms of OFV)
- multiple start values/option to manually change initial values during the process
- check condition number and successful minimisation
- add penalty for recently checked components
- downweigh Michaelis-Menten component
  - investigate overfitting and evaluation approaches

## Conclusion: qPnoMAD can guide popPK model selection

- Parsing less models than an exhaustive search we arrive at a fit-for-purpose model
  - qPnoMAD tested between 20 and 35 models in total
  - In comparison, Pharmpy often tests more than 100 models
- While the true models were not identified in the test cases, the secondary PK parameters were accurate
- Model building approach mimics a trained pharmacometrician's process and can be interpreted similarly
- Opportunity to speed up initial model development considerably to focus on manual refinement and further modelling

## Contact:

undine.falkenhagen@qpharmetra.com collaborations@qpharmetra.com



#### References:

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- [3] Chen X, et al. A fully automatic tool for development of population pharmacokinetic models. CPT Pharmacometrics Syst Pharmacol. 13: 1784-1797. (2024)