

A Comparison of a Genetic Algorithm-Based Automated Search Algorithm to Standard Stepwise Approach for Population Pharmacokinetics using NONMEM Robert R. Bies^{1,2}, Jeffry A. Florian Jr.¹, Bruce G Pollock², Kristin Bigos³, Marci Chew⁴, Yuyan Jin¹, Yan Feng⁵,

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Objective

To compare, using the AIC, the selection of model structures, covariates, covariate relationships, and error structures in models chosen for five separate drugs using both stepwise or genetic algorithm (GA) approaches.

Introduction

- Model search strategies in pharmacokinetic/pharmacodynamic (PK/PD) modeling involve numerous decisions from the modeler
- ★ selection of the appropriate model structure (compartments and parameterizations)
 ★ covariates and covariate relationships
 ★ error structure selection

Genetic Algorithm

- \bullet GA fitness function penalties are shown in Figures 1 and 2
- Fitness of models was evaluated based on penalty function
- $\star\, {\rm objective}$ function plus penalties from the options
- * combination of posterior predictive check (PPC) and normalized predictive distribution errors (NPDE)
- $\star \mathrm{AIC},$ eigenvalues, objective function value, and other criteria
- Downhill search and niche evaluation every 5 generations
- Selection of the next population generation was based on a random selection from the previous generation, weighted according to fitness function values
- Niche membership selects all model pairs differing by < N bits \star all bit combinations between the top models within a niche are then

Cross over/genome	0.7	🔲 Default	NONMEM version
Mutation rate	0.01	🔲 Default	
Theta Criteria	10	🔲 Default	NONMEM VI
Omega criteria	10	🔲 Default	Save control file
Sigma criteria	10	🔲 Default	Save output file
Covariance criteria	400	🔲 Default	Include ga for non diagonal UMEGA
Penalty for corr > 0.95	300	🔲 Default	Count no Sig Digs as Crash?
Minimization Success Criteria	400	🔲 Default	Downhill
Upper limit of scaled fitness	4	🔲 Default	Downhill every 5 generations?
Lower limit of scaled fitness	0.2	🔲 Default	✓ Terminal Downhill?
Population size	200	🔲 Default	
Generation limit	50	🔲 Default	Davideo estad
Max number of effects	99	🔲 Default	Use Default
Lower limit for non-crash	-99999999	🔲 Default	C Use Clock
Method = 0 penalty	200	🔲 Default	C User Defined
Minimization timout (minutes)	0	🔲 Default	☐ Auto Reset Timeout?
Update time limit (minutes)	0	🔲 Default	Re Randomize after 10 generations?
Covariance time (minutes)	0	🔲 Default	Use Tip of the day
Eigenvalue penalty	100	🔲 Default	✓ Use Best Linear Combination
		4	
	Done		Cancel

Figure 1: GA fitness function options

Ę	3 GA options			
ĺ	Basic	Niches	PPC/ NPDE	

- Discrete search space which can not be fully evaluated using conventional approaches
- Initial model structure and order of covariate inclusion can influence downstream results (Wade *et al.* 1994)
 * error structures (additive, proportional)
- * covariate relationships (proportional, power-law, Michaelis-Menten, Hill)
- \star addition of covariates and error relationships are not necessarily linear in reducing error
- Exploration of entire search space is impractical due to time constraints
- GA approach may help address these issues (Bies *et al.* 2006)
- \star capable of running without direct supervision \star criteria for assessing model accuracy essential

Methods

• The following drugs were evaluated: citalopram, perphenazine, olanzapine, quetiapine, and risperidone

Table 1: Data and stepwise model summary for the five compounds

Compound	# patients	# data points	Model structure	Covariates
citalopram	331	1324	2-comp., intravenous	10

evaluated

- Model with the highest fitness carried to the next generation
- First-order estimation with interaction for all models
- NONMEM VI with Intel Fortran (VERSION 9.1)
- Performed on 10 Dual Core Computers
- \bullet GA search summary and search convergence are shown in Figures 4 and 5
- Stepwise versus GA performance was assessed using model predicted AIC



Figure 5: GA search convergence profile **Results**



Figure 2: GA PPC and NPDE options

3 GA options			
Basic	Niches	PPC/NPDE	
🔽 Use Niches			
Number of niches	Default		
Niche radius (Hamming distance) 6	Default		
Save Best in Niche?			
Niche Penalty			
C Scaled (fraction of best-nonnic	he) 🛛 🗖 Defaul	t	
Fixed	100		

Figure 3: GA niche options

GA versus Standard Approach

Table 2: Summary of model results using both stepwise or GA approaches

	many or		Salos asi	118 20011 20			
Compound	Search	AIC	OBJ	$\left \left \theta \right \right \eta \left \epsilon \right $	Covariates	Δ AIC	Comments
oitalonram	Stop	5712.0	5600 0	8 2 2	CL (woight) O (fat maga) Va (woight gov)		no coverience stop

CL (age, sex, race, other meds), V (sex)

			combined error		citatopiani	Ducp	0110.0	0000.0		C L (Weight), & (Iau IIIabb), V (Weight, ber)		no covariance step
perphenazine	156	421	1-comp., oral	8						CL (sex, weight, body mass index, fat mass)		
			proportional error			GA	5345.9	5304.9	17 3 1	V_1 (sex, body mass index, free fat mass)	367.1	covariance step converged
olanzapine	523	1527	1-comp., oral	7						Q (sex, free fat mass), V_2 (sex, weight, free fat mass)		
			additive error		perphenazine	Step	561.9	537.9	12 3 1	CL (race, smoking status, other meds)		k_a not estimated
quetiapine	405	945	1-comp., oral	7		GA	556.9	531.9	10 1 1	CL (race, # cigarettes, smoking status, other meds)	5.01	covariance step with k_a
			additive error							V (age, sex, smoking status)		
			1- or 2-comp. mixture	e 7	olanzapine	Step	10365.8	10347.8	6 2 1	CL (sex, smoking status, race)		
risperidone	490	1236	model, intravenous	3 CL groups		GA	9850.8	9832.8	6 1 2	CL (sex, smoking status, race)	515.0	different error structures
			combined error		quetiapine	For.	11126	11110.4	4 3 3	V (weight)		k_a not well estimated
• Search space was restricted to those originally			GA	10114	10095.7	3 2 2	no significant covariates	1014.7	estimated k_a , no covariates identified			
considered during the initial model evaluation		risperidone	Step	5119.1	5103.1	$\begin{array}{ c c c } 7 & 5 & 4 \end{array}$	no significant covariates		3 CL group mixture model			

★ all model structures (compartments and/or mixtures), covariates, covariate relationships, and output error metrics

- $\star 6$ relationships for continuous covariates and 4 for discrete covariates
- $\star 3$ interindividual variability structures (exponentiated, proportional, additive)
- $\star 3$ residual unknown variability structures (additive, proportional, combined)
- \star risperidone analysis included a mixture model option

COVAACL

• Example code with token sets shown below

Number	of	models	=
1			

Risperidone

4694.9 4662.9 11 3 2

- \bullet GA search included the possibility of one, two, or three groups for parent compound CL
- \star only two CL groups were identified
- $\star\, \mathrm{improvement}$ over the previously developed model
- \bullet GA identified significant covariates on CL and V
- \star age, sex, race, and other medications
- Sample code shown below

GA

\$MIX P(1)=THETA(3)/(1+THETA(3)) P(2)=1-P(1) NSPOP=2 ¢PK TVV1 = THETA(1) TVV2 = TVV1 *EXP(ASEX*THETA(11)) TVV3 = TVV2 V = TVV3 *EXP(ETA(2)) KA-THETA(2)

Olanzapine

2 CL group mixture model

424.2

- Same number of parameters and significant covariates
- Differences between the models included
- * interindividual variability (k_a and CL vs. CL) * output error (additive vs. proportional and additive)
- Estimate of k_a possible with GA

Summary

• GA search resulted in a lower AIC than stepwise for all five drug models

########### Begining of model # 1 #################################	N token sets = 4 N tokens =
\$INPUT ID DATE=DROP TIME AMT RATE DV MDV CMT SS II SEX SMOK AA AGE WT	2 Check syntax =
\$DATA FINALDATASET8.CSV	False IS IOV OMEGA =
\$SUB ADVAN=ADVAN2 SS=SS2 TRANS2	False N IOV OMEGA =
\$PK	0 Token set #
<pre>TVCL5 = THETA(1) TVCL4 = TVCL5 COVSEXCL(1) TVCL3 = TVCL4 COVSMOKCL(1) TVCL3 = TVCL4 COVSMOKCL(1) TVCL = TVCL1 COWTCL(1) CL = TVCL1 COWTCL(1) CL = TVCL1 COWTCL(1) CL = TVCL1 COWTCL(1) TVVE = THETA(2) TVVE = THETA(2) TVVE = TVVE COVSEXV(1) TVVE = TVVE COVSEXV(1) TVVA = TVVB COVSMOKV(1) TVVA = TVVB COVAQU(1) TVV = TVVA COWTV(1) V = TVV VERR(1) TVVA = TVFA COWTV(1) V = TVV VERR(1) TVKA = THETA(3) KA = TVKA S2 = V IF(MDV.EQ.0.AND.TIME.GE.0.AND.TIME.LE.24) THEN PPCI = 1 ELSE PPCI = 0 END IF RP = IREP \$ERROR Y=F RESERR(1) IPRED=F OB = DV ; FOR NPDE PROBLEM 1 Y = F RESERR(1) FSIM = Y ; FOR NPDE PROBLEM 1 Y = F RESERR(1) FSIM = Y ; FOR NPDE PROBLEM 2 \$THETA (1.18.50) ; CL COEFF (100.3000,8000) ; V COEFF (100.3000,8000) ; V COEFF (100.3000,8000) ; V COEFF (100.05.0.5.5) ; KA COVSECL(2) COVAACL(2) COVAACL(2) COVAAC(2) COVACEV(2) COVAAC(2) COVAAC(2) COVACEV(2) COVAAC(2) COVAAC(2) COVACEV(2) COVAAC(2) COVACEV(2) COVAAC(2) COVACEV(2) COVAAC(2) COVACEV(2) COVACEV(2)</pre>	Token set # 1 Token set # 2 +AA*{THETA(C)} {\$THETA(C)=}(-4,0,01,4) Token set # 3 *(1+AA*{THETA(C)}) {\$THETA(C)=}(-4,0,01,4) Group stem # 4 *EXP(AA*{THETA(C)}) {\$THETA(C)=}(-4,0,01,4) Group stem = COVAGECL N token set # 2 Check syntax = False IS IOV OMEGA = 0 Token set # 1 Token set # 1 Token set # 2 +AGE*{THETA(D)} {\$THETA(D)=}(-4,0,01,4) Token set # 4 *[1+AGE*{THETA(D)}) {\$THETA(D)=}(-4,0,01,4) Token set # 4 *EXP(AGE*{THETA(D)}) {\$THETA(D)=}(-4,0,01,4) Token set # 4 *EXP(AGE*{THETA(D)}) {\$THETA(D)=}(-4,0,01,4) Token set # 5 *{THETA(D)=}(-4,0,01,4){crlf}{\$THETA(E)=}(-4,0,01,4) Token set # 5 *{THETA(D)=}(-4,0,01,4){crlf}{\$THETA(E)=}(-4,0,01,4)} TOKEN 5 *{THETA(D)=}(-4,0,01,4){crlf}{\$THETA(E)=}(-4,0,01,4)} TOKEN 5 *{THETA(D)=}(-4,0,01,4){crlf}{\$THETA(E)=}(-4,0,01,4)}
	*AGE**{THETA(D)} {\$THETA(D)=}(-4,0.01,4)

<pre>\$PK CALLFL =1 AAGE = (AGE-46.6)/16.8 AWT = (WGTB-188)/50 ASEX = SEX-1 EST=MIXEST IF(MIXNUM.EQ.1)THEN BCL=THETA(4) ELSE BCL=THETA(4) ELSE BCL=THETA(5) ENDIF TVCL1 = BCL *EXP(AAGE*THETA(6)) TVCL2 = TVCL1 *EXP(AAGE*THETA(6)) TVCL2 = TVCL1 *EXP(AAGE*THETA(6)) TVCL3 = TVCL2 *EXP(PARX*THETA(9)) *EXP(FLUX*THETA(10)) CL = TVCL3 *EXP(ETA(1))</pre>	<pre>KA=THETA(2) ; ADVAN2 S2=V IF(MDV.EQ.0.AND.TIME.GE.0.AND.TIME.LE.2 PPCI = 1 ELSE PPCI = 0 END IF RP = IREP \$ERROR Y=F *EXP(EPS(1))+EPS(2) IPRED=F OB = DV ; FOR NPDE PROBLEM 1 FSIM = Y ; FOR NPDE PROBLEM 2</pre>
able 3: Summary of GA populationnd total number of identified models	size, generations evaluated,

Compound |# individuals |# generations | unique models |% total 300 21431 0.0549 citalopram 300 0.355013903 perphenazine 200 0.81 508033 olanzapine 200 507231 0.73 quetiapine 400 7948 0.09 risperidone 30 Olanzapine: 3 residual unknown variability, 3 parameters with 3 interindividual variability structures, 5 discrete covariates (4 structures), and 2 continuous covariates (6 structures). Total $\# = 3 * 3 * 3 * 4^5 * 6^2$

★ geometric and arithmetic means of 210 and 465
 Different models predicted by the GA for all cases
 ★ alternate output error structure (4/5)
 ★ different set of parameters with interindividual variability (4/5)
 ★ significant covariates/covariate relationships (4/5)

 \star fewer CL categories were necessary in the risperidone mixture model

Acknowledgements

National Institute of Mental Health Research Grants R01 MH64173, P30 MH30915, R01 MH65376, K24 MH65416, MH52247, N01 MH90001, and MH76420
CATIE investigators (P.I. Jeffrey Lieberman, MD)