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# **Determination of Appropriate SIR Settings** when Assessing Parameter Uncertainty

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## Aim

The objectives of this work were to develop diagnostics to select optimal settings for the Sampling Importance Resampling (SIR) method in terms of:

- number of initial samples
- proposal uncertainty distribution

# Conclusion

• dOFV distributions and bin plots were developed as quantitative and qualitative criteria to determine whether SIR settings are optimal

## Methods

#### Application to real data examples

Three real data examples [3-5] were used to investigate the relevance of the proposed diagnostics in the choice of optimal SIR settings.

Table 1 Summary of investigated SIR settings and diagnostics used to select the most appropriate ones

| SIR setting                                      | Alternatives tested          | Diagnostics       |
|--|------------------------------|-------------------|
| Number of initial samples                        | 200, 4000, 6000, 8000, 10000 | dOFV distribution |
| Proposal uncertainty distribution                | 0.5, 0.75, 1, 1.5, 2 *COV    | Resampling plots  |
| COV is the asymptotic variance-covariance matrix |                              |                   |

# Results

- These criteria are easy to use and will facilitate reliable use of the SIR method
- SIR is readily implemented in PsN [6] and the diagnostics are being added. Automation of the choice of settings based on these criteria is under investigation

# Background

SIR [1] has been proposed as a method for assessment of parameter uncertainty in nonlinear mixed effects models [2]. The advantages of SIR are:

- no repeated parameter estimations
- no distributional assumptions

• applicability to many situations in which other methods fail (limited data, meta-analysis) SIR always constitutes an improvement over the proposal distribution, but it is only guaranteed to reflect the true uncertainty when the number of initial samples is high enough in relationship to the adequacy of the proposal density. The question of whether SIR settings are optimal, or how close the results are from the true uncertainty, needs to be addressed.

# **Methods**

### SIR principle

The objective of SIR is to provide a given number *m* of parameter vectors which are representative of the true uncertainty distribution based on a given number M (M > m) of parameter vectors simulated from a proposal uncertainty distribution. The *m* vectors can

#### Number of initial samples



SIR 2000 - SIR 4000 - SIR 6000 - SIR 8000 - SIR 10000 - Covariance matrix - Reference chi-square

**Figure 1**. Comparative dOFV quantile distributions for the proposal density (blue), SIR with increasing number of initial samples (colors) and the reference chi-square (black) for the three real data examples.

- SIR dOFV stabilized after a number of initial samples dependent on the proposal density (between 4000 and 8000 when starting from the uninflated covariance matrix) The level of stabilization was dependent on the proposal density
- Stabilization of the dOFV curves correlated well with stabilization of the 95% confidence intervals at the parameter level (data not shown)

#### then be used to compute confidence intervals or as input for simulation.



#### **Developed diagnostics**

|             | dOFV distribution  | Resampling plots  |
|-------------|--|---|
| Description | Plot dOFV value versus dOFV quantile for<br>SIR, the proposal density and the<br>reference chi-square. Can be<br>summarized numerically by taking the<br>integrand of the area under the dOFV<br>quantile curve ( $dOFVint$ ).<br>$dOFVint = \int_{0.025}^{0.975} dOFV d(q)$ | Initial percentile plot : divide the parameter space<br>defined by the initial samples into 10 equally sized<br>percentile bins. Calculate and plot the proportion of<br>parameters resampled by SIR in each bin.<br>Resamples percentile plot : for the bin with highest<br>proportion in the initial plot, calculate the proportion<br>of resamples for 10 subsets of the resampled<br>parameters sorted by sampling order. |
| Level       | Global (1/model)   | Local (2/parameter)   |
| Example     | dOFVint<br>Proposal density 13.57  | CL KA IIV CL RUV  |

#### **Proposal density**



Figure 2. Resampling plots (initial in top panel, resamples in bottom panel) for the moxonidine example using SIR settings of no inflation and 10,000 initial samples. The horizontal lines are the expected proportions, the grey shaded areas are the stochastic noise.

- The appropriateness of the proposal density is parameter dependent
- Deviations from the proposal density were observed for KA, TLAG and random effects
- SIR was able to compensate these deviations except for TLAG

#### **Proposed workflow**

Perform SIR using the best available proposal density and a number of initial samples 5 to 10 times the desired number of resamples.



Expected behavior under the true uncertainty Interpretation

The dOFV follow a  $\chi^2$ -distribution with degree of freedom equal or slightly inferior to the number of estimated parameters.

*dOFVint* higher than the reference indicates less than optimal conditions. The number of initial samples should be so that further initial samples do not change the dOFV distribution.

The proportion of resampled parameters should be similar (up to stochastic noise) in each bin. SIR is able to compensate trends if the proportion stays similar over the resamples percentile bins.

RUV

INIT BIN 6

- Trends in initial percentile plot (top panel):
  - Horizontal : proposal density appropriate
- U-shaped : proposal density too narrow
- Diagonal : presence of asymmetry
- Bell-shaped : proposal density too wide Trends in resamples percentile plot (bottom panel):
- Horizontal : SIR appropriate
- Diagonal descending : SIR can be improved

- Based on the dOFV distribution, judge whether the number of initial samples is appropriate, i.e. whether convergence is achieved. Based on the initial percentile plot, check if the proposal density is appropriate for the parameters. If not, check the resamples percentile plot to see if SIR could compensate.
- 3. If SIR could not compensate for the inadequacy of the proposal density, perform SIR with an updated proposal density and/or increased number of initial samples. Updating the proposal density appeared most efficient in the investigated examples.

#### References

[1] Rubin DB, Bayesian Statistics. 1988;3:395-402 [2] PAGE 22 (2013) Abstr 2907 [www.page-meeting.org/?abstract=2907] [3] Karlsson et al., J Pharmacokinet Biopharm. 1998;26(2):207–46 [4] Wählby et al., Br J Clin Pharmacol. 2004;58(4):367–77 [5] Grasela et al., Dev Pharmacol Ther. 1985;8(6):374-83 [6] Lindbom et al., Comput Methods Programs Biomed. 2004 Aug;75(2):85-94.



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