A PARAMETER ESTIMATION SYSTEM WITH COMPUTATIONAL ADVANTAGES FOR FITTING PROBABILISTIC DECOMPRESSION MODELS TO EMPIRICAL DATA

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INTRODUCTION

- Probabilistic decompression models differ from deterministic models in that parameters are optimized against empirical dive data[1].
- The method of likelihood maximization is used to optimize model parameters.
- Time of onset of DCS symptoms can be used to further refine and test candidate DCS models[2].
- OBJECTIVE: To create a fast computer system for optimizing DCS models and validate the system against earlier work.

METHODS

- Our object-oriented DCS model optimization system is written in C#.NET (2005).
- Nine different numerical optimization methods (seven gradient-based) are available for model optimization and testing.
- NMRI format dive data is handled and manipulated automatically.
- Optimization of four previously published models (EE_1(nt), EE_1, LE_1(nt), LE_1) used a data set of 2383 exposures resulting in 131 instances of DCS and 75 instances of marginal DCS[3].
- Parallel processing and cluster computing capabilities are included to accelerate model optimization.
- Standard error and confidence interval calculations are included to evaluate models.

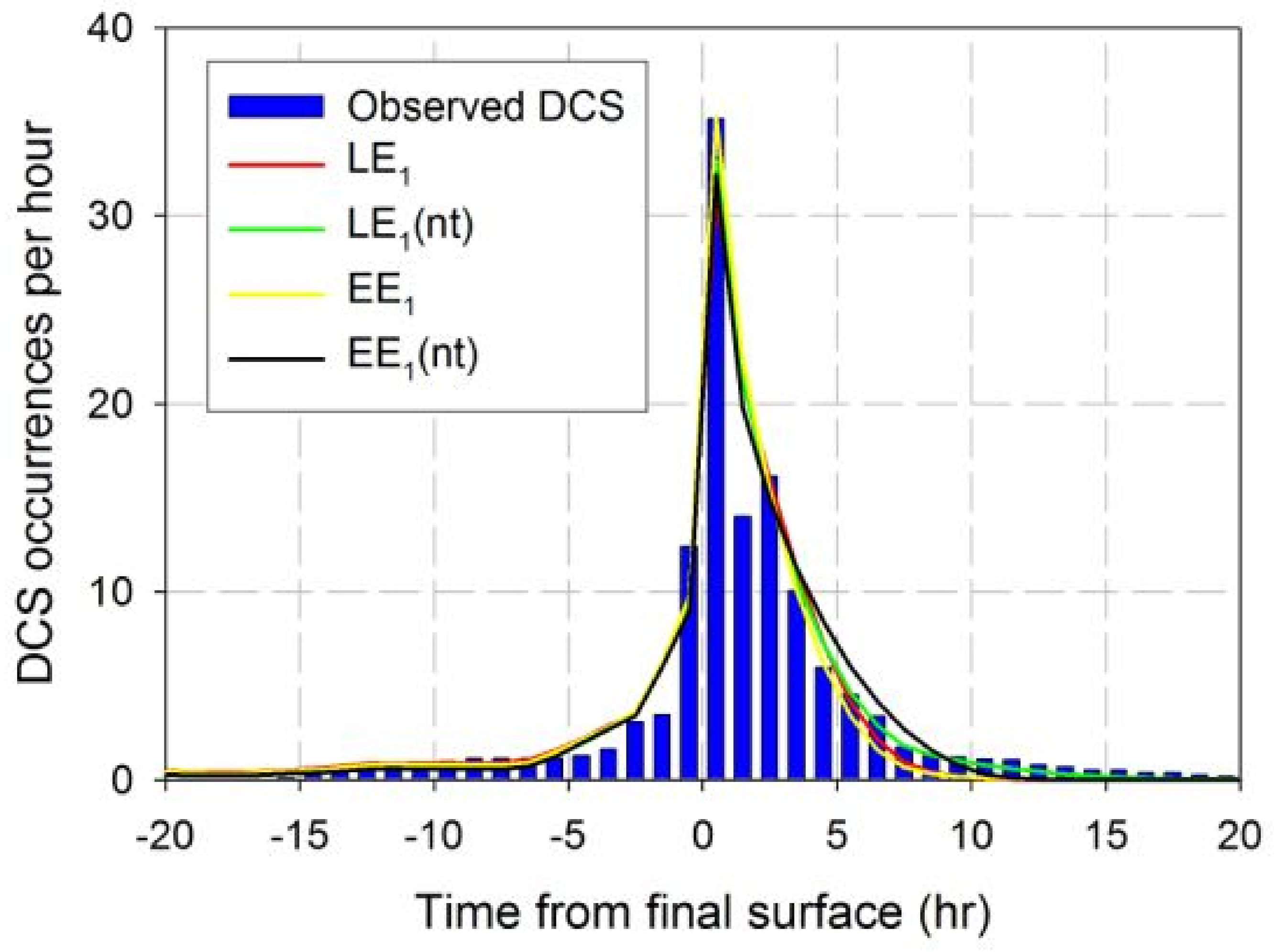

Figure 1. Occurrence density functions for four re-optimized DCS models.

RESULTS

- Figure 1 Occurrence density function of observed DCS onset times compared with re-optimized model predictions (2383 exposures[3]). We were able to reproduce earlier models[3] to within one log likelihood (LL) unit.
- Figure 2 Ternary plot showing the relative risk contribution for the three-compartment LE_1 model (Temple[4] data set, 8578 exposures).
- Table 1 Average model optimization time, DCS predictions and LL_{max} for the LE_1 model. The data included 138.5 DCS cases (with marginal DCS). The Levenberg-Marquardt method was not robust. The BFGS* method offered the best combination of optimization speed and solution robustness.

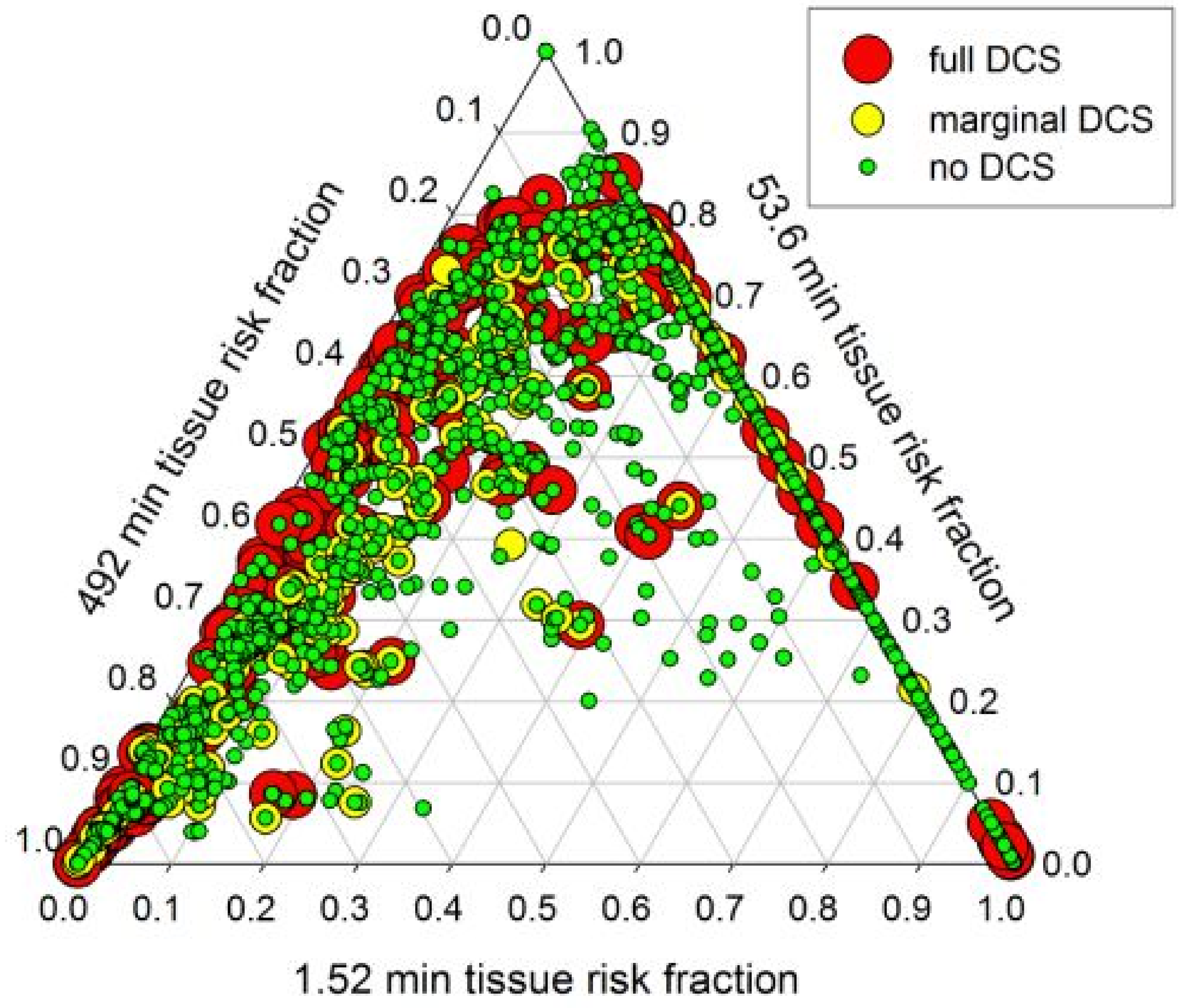

Figure 2. Ternary plot of fractional tissue compartment DCS risk – Temple Data Set[4]. A profile with equal risk contribution from each tissue compartment would fall at the plot center.

Method	Average Time (min)	Predicted DCS	LL_{max}
Nelder-Mead	633.38	90.59	-838.1
Cauchy Steepest Ascent	110.06	130.94	-699.3
Fletcher-Reeves	40.44	138.45	-697.0
Positive Polak-Ribière	35.89	138.44	-697.0
Polak-Ribière	35.64	138.44	-697.0
Broyden-Fletcher-Goldfard-Shanno*	27.41	138.37	-697.0
Powell	26.74	138.46	-697.0
Davidon-Fletcher-Powell	24.13	138.76	-697.0
Levenberg-Marquardt – **not robust**	0.21	134.13	-697.1

Table 1. Average performance of optimization methods for the full LE_1 (12 parameter) model.

DISCUSSION AND CONCLUSIONS

- Fast optimization and evaluation of probabilistic DCS models allows for multiple initial starts in search of a candidate optimal parameter set.
- NMRI format dive data[4] can be extended to include information on DCS severity, immersion, dive conditions (such as temperature), and exercise level for advanced model development.
- Computationally expensive models can be reduced by eigen-mode expansion, system identification, or principal component analysis.
- Our optimization system is parallel processor and/or grid computing capable. The optimization speed scales slightly sub-linearly with the number of processors.
- False maximum log likelihood solutions that result through an n-dimensional saddle node are trapped.
- We will use this system for new DCS model development, optimization, and evaluation. We plan to investigate pharmacokinetic models and models including the effects of DCS severity and dive conditions.

REFERENCES

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ACKNOWLEDGMENT

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