

Application of Neural Networks in LS-OPT: Parametric Study and Guidelines

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> 3rd German LS-DYNA Users Meeting Bamberg, Germany October, 2004

Overview

- Metamodeling Methods
 - > Goals
- Optimization
 - > Technologies
- Examples
 - > Frontal Crash: full vehicle
 - ➤ Knee Impact
 - > Analytical Benchmarks
- Conclusion

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How are metamodels used in crash?

Surrogate model for design

- Approximations critical for design modeling in <u>nonlinear</u> <u>dynamics</u> (LS-DYNA)
- > Global approximation: Optimization & Tradeoff
- Model for any number of simulation runs
 - <u>Given</u>: number of simulation runs <u>Required</u>: Surrogate model
 - Different polynomial orders require discrete numbers of runs (e.g. 10var: L=11+, Q=66+)
 - Adding points to a simple model (linear) does not significantly improve the prediction accuracy
- Local improvement
 - > Refine regionally, but maintain global relevance

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Technologies for Optimization

- Metamodels
 - Response Surface Methodology
 - > Feedforward Neural Networks
- Point selection:
 - > RSM: *D*-Optimal
 - NN: <u>Updated Space Filling</u> (Maximize Min. Distance between any two points) Johnson (1990)
- Subdomain Reduction
 - > Reduce the region of interest for each iteration
 - Heuristics: Roux/Stander *et al* (*MA&O* 1996, *IJNME* 1998, Crash & Benchmarking: *EC* 2002)
 - > RSM: Necessary for low order polynomials: regional approximation
 - > NN: Necessary for regional refinement. Start with full design space
- Simulation (LS-OPT)
 - > Parallel or distributed
 - Automated

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Metamodeling Methodology

- Response Surface Methodology (RSM)
 - > Polynomial-based (only linear in this study)
 - Point selection: <u>D-Optimality</u>
 - > <u>Regional</u> (midrange) approximation
- Neural Nets
 - > Simulation of a biological network
 - > Nonlinear Regression (Levenberg-Marquardt, BFGS,...)
 - > Point Selection: <u>Updated Space Filling</u>

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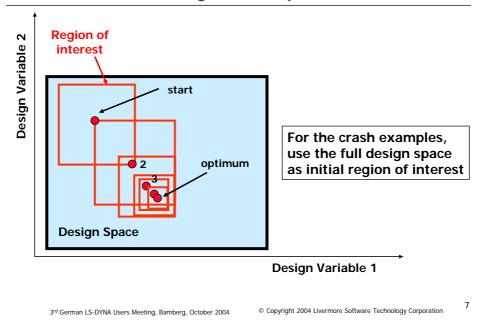
Point Selection

- NN
 - > Space Filling
 - > <u>Simulated Annealing</u> to locate new points
 - > Max. Min. distance between
 - new points
 - new points + fixed points
 - > New points bounded by <u>sub-region</u>
 - > 1.5(*n*+1) points per iteration: relatively sparse

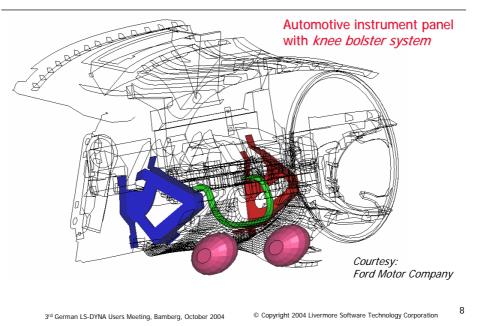
Response Surface Method

- ▹ Use D-Optimality (GA)
- linear approximations
- > 1.5(*n*+1) points per iteration

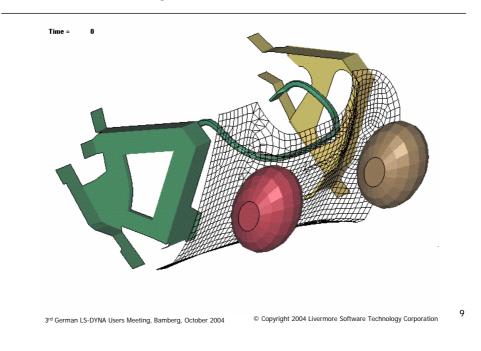
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Successive Approximation Scheme Converges to an Optimum

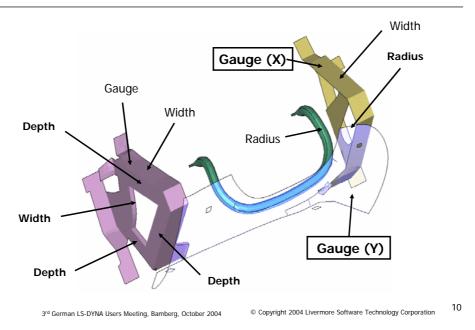


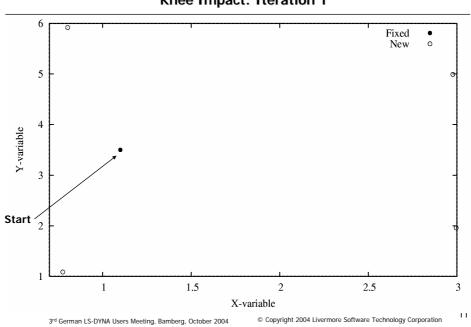
Components to Be Designed



40ms Impact: LS-DYNA Simulation

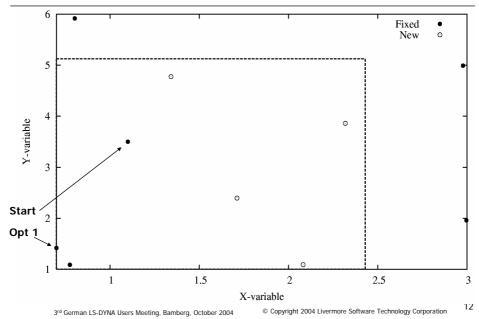


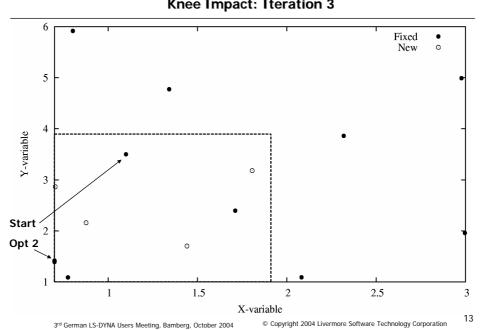






Experimental Design: Space Filling Method Knee Impact: Iteration 2





Experimental Design: Space Filling Method Knee Impact: Iteration 3

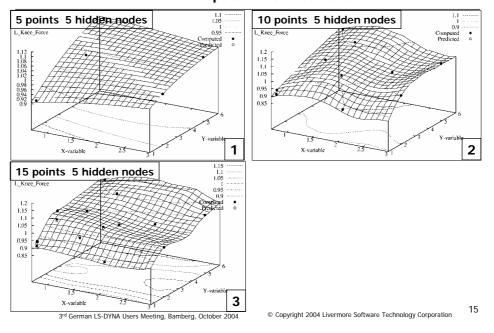
Feedforward Neural Networks

- Construct *ensemble* of architectures (different numbers of hidden nodes)
 - > Single layer architectures (0 10 nodes)
 - Select the "best" net
 - > Selection criterion: Min. <u>Generalized Cross Validation</u> (GCV)

Some properties of NN Variance Modeling

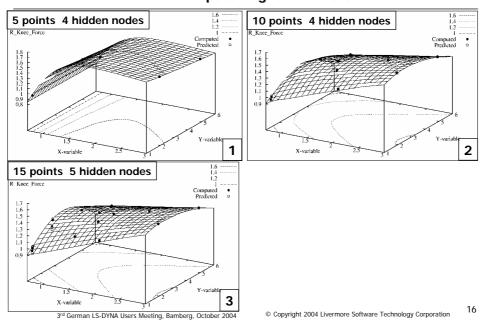
- NN's have variance due to local minima associated with training
- Net variance is bigger for noisy functions and for extrapolation

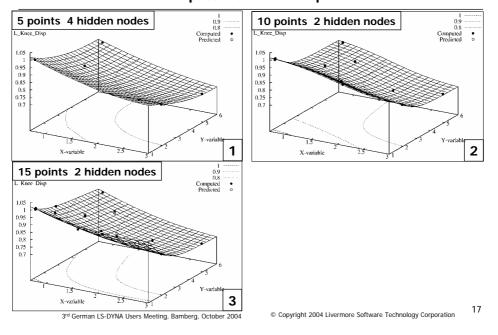
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Neural Network Updating Knee Impact: Left Knee Force

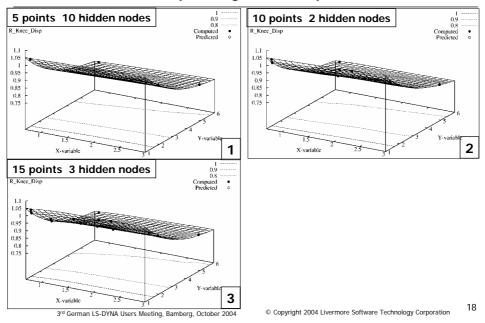
Neural Network Updating Knee Impact: Right Knee Force

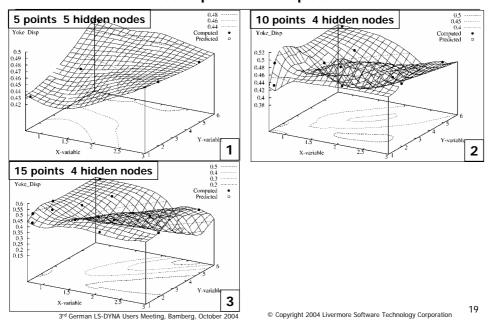




Neural Network Updating Knee Impact: Left Knee Displacement

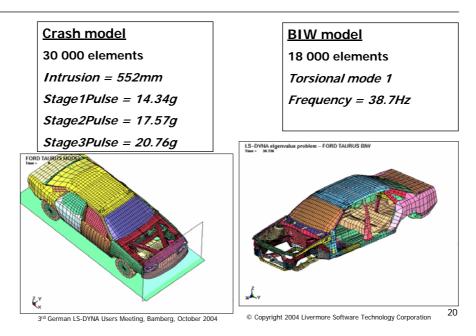
Neural Network Updating Knee Impact: Right Knee Displacement

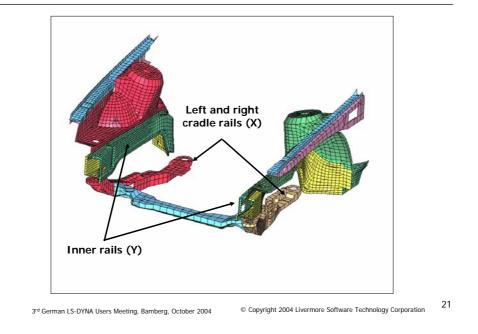




Neural Network Updating Knee Impact: Yoke Displacement

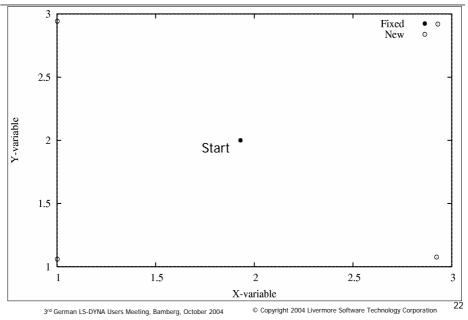
Crash Performance of Base Design

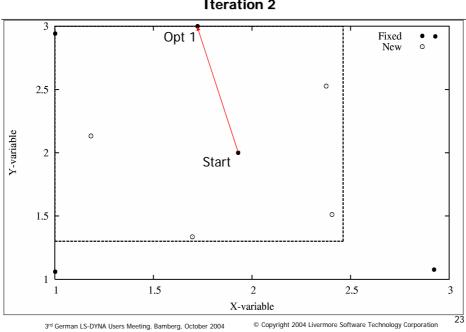




Two Design Variables (Thickness)

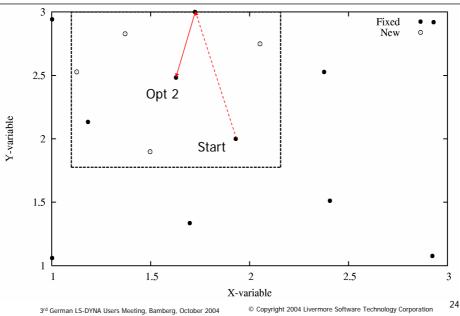


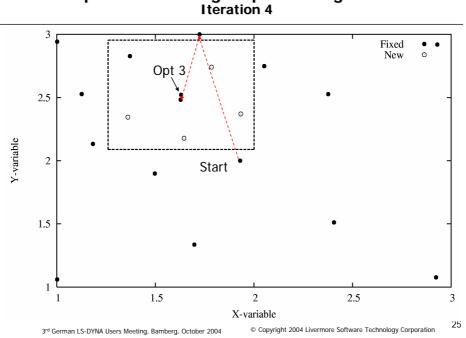




Experimental Design: Space Filling Method Iteration 2

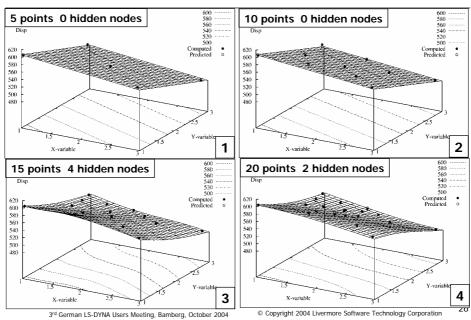


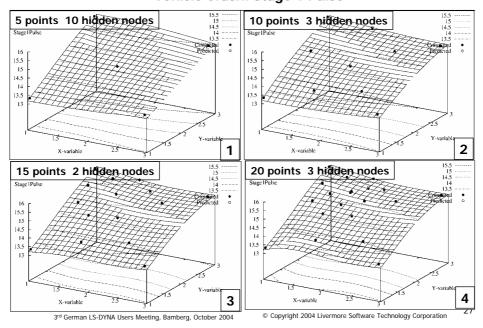






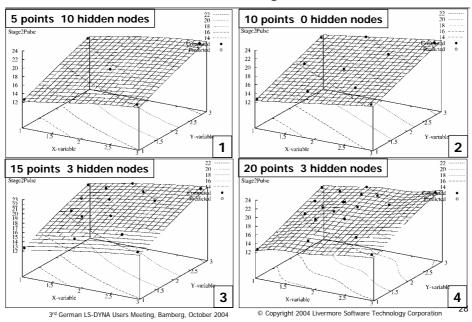
Neural Network Updating Vehicle Crash: Intrusion

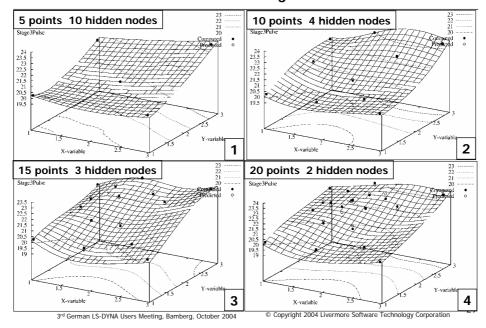




Neural Network Updating Vehicle Crash: Stage 1 Pulse

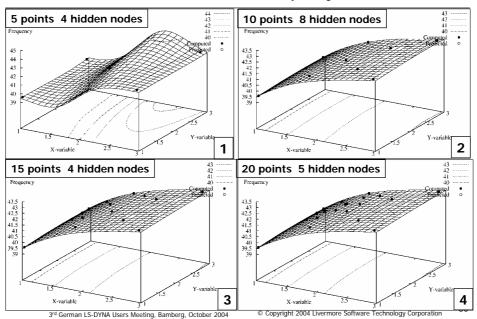
Neural Network Updating Vehicle Crash: Stage 2 Pulse

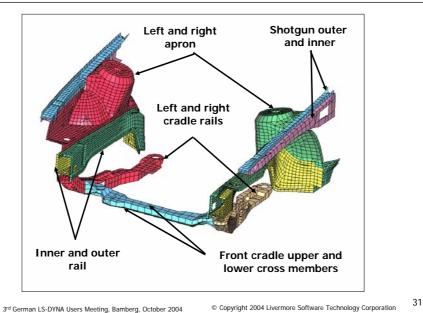




Neural Network Updating Vehicle Crash: Stage 3 Pulse

Neural Network Updating Torsional Mode: Frequency



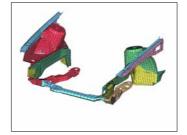


Optimization Design Variables (Thickness)

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Design Formulation (MDF partially shared variables)

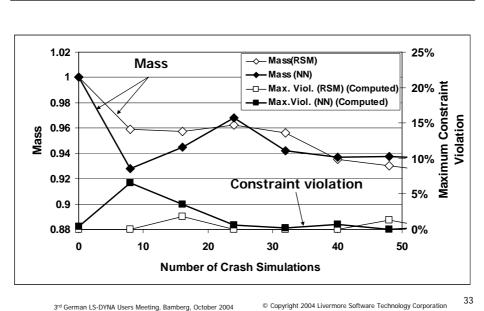
Design Objective: Minimize (Mass of components) **Design Constraints:** Intrusion < 552.38mm Stage1Pulse > 14.58g Stage2Pulse > 17.47g Stage3Pulse > 20.59g 41.38Hz < Torsional mode 1 frequency < 42.38 Crashworthiness design variables: 4 Rails (inner and outer); Aprons; Cradle rails NVH design variables: 7 (all)



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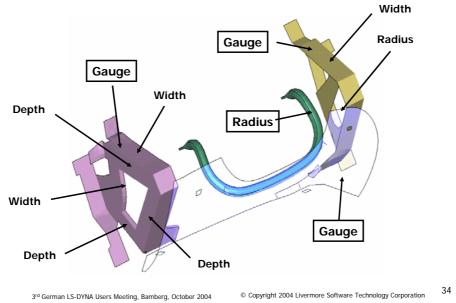
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Full vehicle Optimization History

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Design Variables



Design Formulation

Design Objective:		
min (max (Knee_F_L, Knee_F_R))		
Design Constraints:		
Left Knee intrusion	<	115mm
Right Knee intrusion	<	115mm
Yoke intrusion	<	85mm
<u>Design variables</u>		
Reduced from 11 to 4 (ANOVA)		

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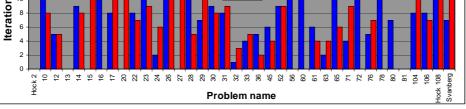
1.4 □ L Knee Force (RSM) L Knee Force (RSM) (pred) 1.3 △ R Knee Force (RSM) R Knee Force (RSM) (pred) L Knee Force (NN) 1.2 Knee Force L Knee Force (NN) (Pred) Δ ▲ R Knee Force (NN) R Knee Force (NN) (Pred) 1.1 Δ **,** Г 1 Ł 0.9 0.8 8 24 0 16 32 40 48 **Number of Simulations** 36

Optimization Convergence

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Additional Benchmarks for Testing NN 37 Hock & Schittkowski, Svanberg Polytope

Polynomials of various orders
 Exponential functions
 Svanberg Polytope (21 var.)
 2 – 21 variables
 Number of iterations for 1% accuracy
 Omission: not converged within 15 iterations



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Guidelines for Optimization with NN

- Use full design space as initial region of interest by simply omitting <u>initial range</u> (in "Variables" panel)
- Iterative updating: Use same number of <u>points per</u> <u>iteration</u> as linear response surface.
- Use <u>Space Filling</u> sampling method (<u>default</u>)
- Make sure that "Updated" Neural Net Option is set ("Sampling" panel) (<u>default</u>).
 - > Effect: Points will be placed in Maxi-min. Positions
 - > Metamodeling will be done using all available points

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Advantages of NN

Global approximation

- > Avoids inaccuracy for small range does regional refinement
- Can apply trade-off study or robustness analysis after optimization run
- Do not have to choose between different orders of polynomials.
 - > Choice of NN architectures is automated
 - Independent of number of points chosen (so can choose minimum, e.g. as for linear)

Do not have to choose initial range

- > Start with full design space
- A regression method not interpolation
 Filters noise

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