Optimization of Visco-Elastic Material Models of Mold Compounds Used in Electronic Packages Based On Evolutionary Algorithms

Weimarer Optimierungs- und Stochastiktage 4.0
29.-30. November 2007

Axel Mueller[1], Sven Rzepka[1], Johannes Will[2]
[1]Qimonda Dresden GmbH & Co. OHG, [2]Dynardo GmbH

Pilot Project w/ Dynardo

Simulation Task

Parameter Identification

Conclusions

Pilot Project w/ Dynardo

Simulation Task

Parameter Identification

Conclusions

Pilot Project w/ Dynardo

Application Of *optiSLang* To Material Modeling Tasks

Task I: ANSYS
identification of visco-elastic material data

- calibration of quasi-static data
- many parameters (> 20)
- simulation time ~10 min / leg
- optiSLang ⇔ ANSYS

Task II: LS-DYNA
identification of rate-dependent solder data

- calibration of noisy data
- few parameters only (< 10)
- simulation time ~1 h / leg
- optiSLang ⇔ LS-DYNA

Topic Of This Presentation

Pilot Project w/ Dynardo

Simulation Task

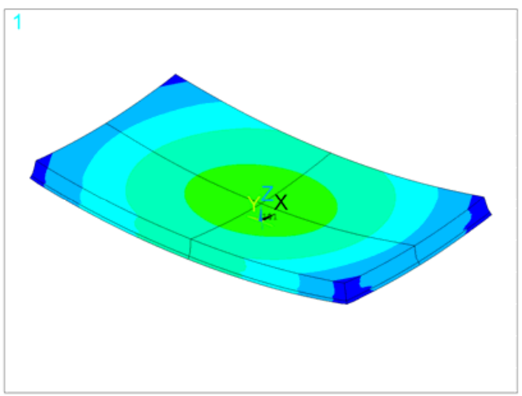
Parameter Identification

Conclusions

Simulation Task

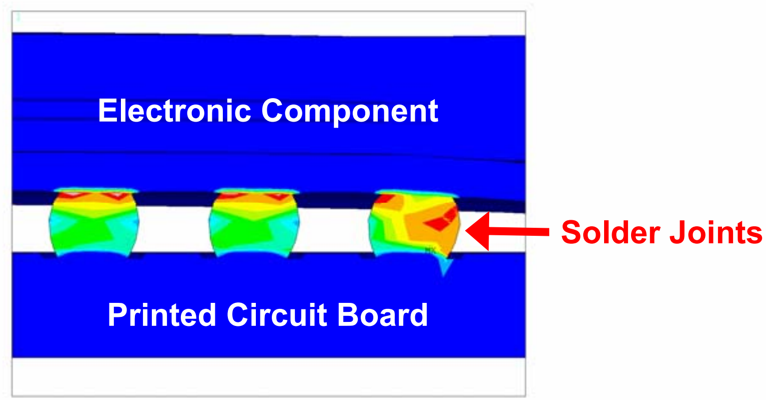
Microelectronic Packages Exposed To Temperature Loads

Manufacturing



E.Q. Component Warpage
During Solder Reflow?

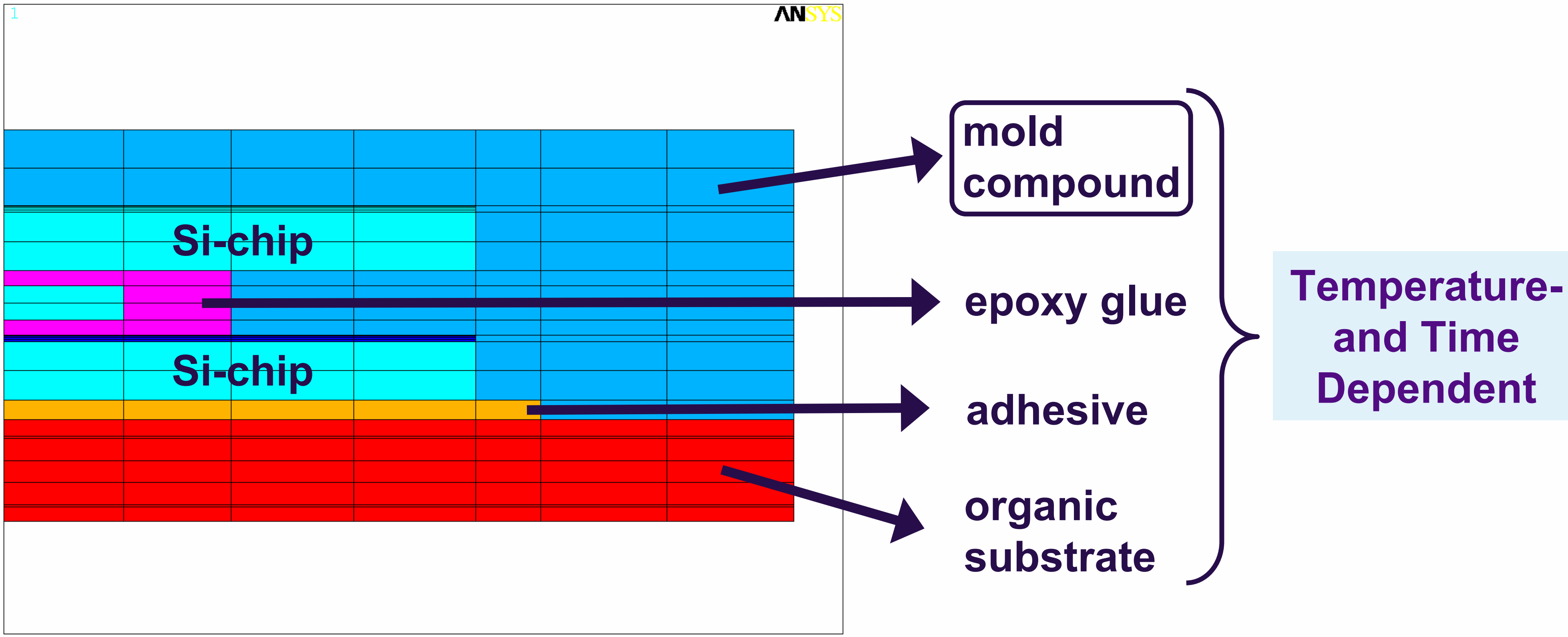
Operating Condition



Thermal Cycle Test (JEDEC Standard)
→ Solder Joint Reliability?

Challenge

Multi-Layer Structures Composed of Complex Materials

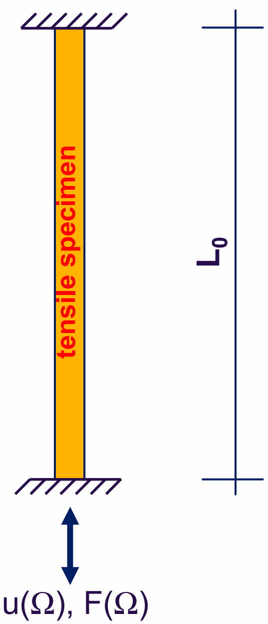


Material Characterization

Dynamic Mechanical Analysis (DMA)

Parameter:
temperature T,
frequency f

Frequency Data:
storage modulus E'(T),
loss modulus E''(T)



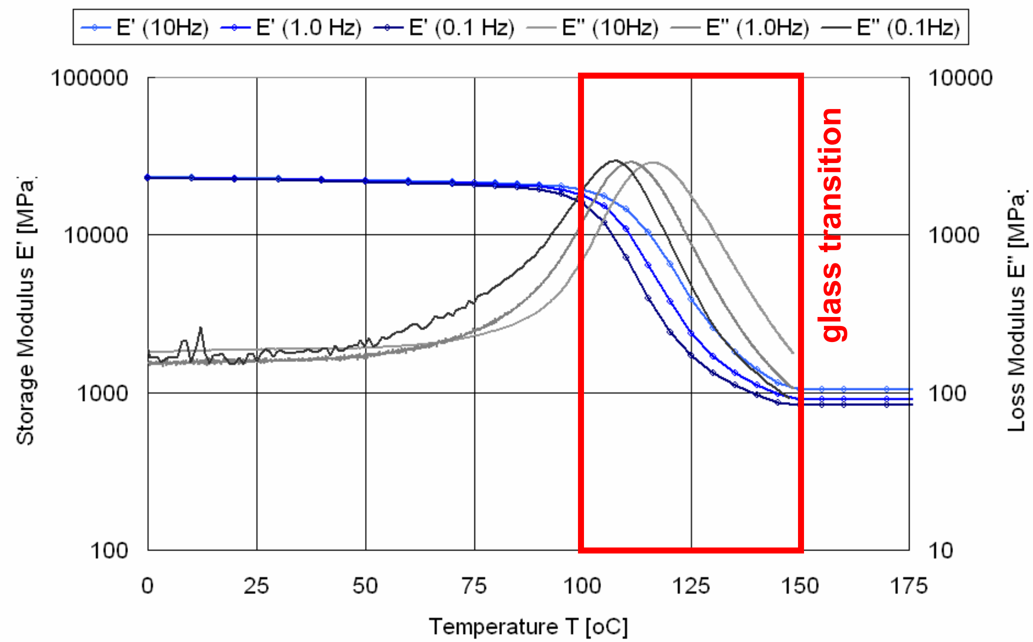
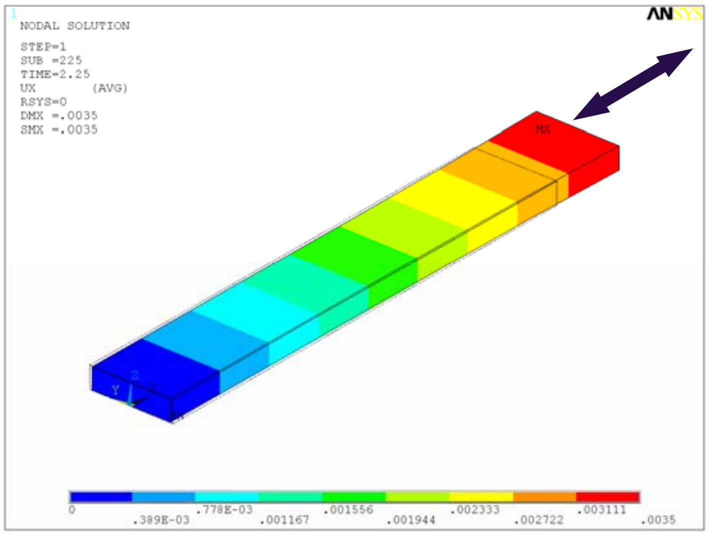


Fig. 1: Tensile Specimen w/ Sine Load

Fig. 2: Frequency Dependent E-T-Profiles

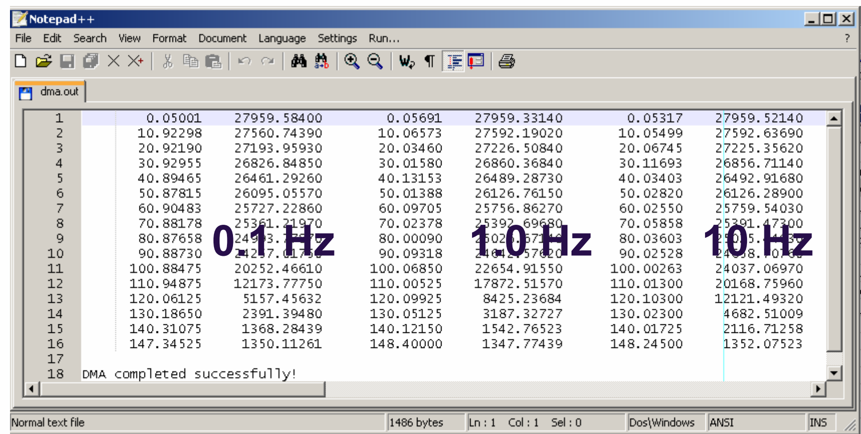
Material Modeling

Parameterized Finite Element Model of the Test



~10 min

1 vector for each frequency



1	0.05001	27959.58400	0.05691	27959.33140	0.05317	27959.52140
2	10.92298	27560.74390	10.06573	27592.19020	10.05499	27592.63690
3	20.92190	27193.95930	20.03460	27226.50840	20.06745	27225.35620
4	30.92955	26826.84850	30.01580	26860.36840	30.11693	26856.71140
5	40.89465	26461.29260	40.13153	26489.28730	40.03403	26492.91680
6	50.87815	26095.05570	50.01388	26126.76150	50.02820	26126.28900
7	60.90483	25727.22860	60.09705	25756.86270	60.02550	25759.54030
8	70.88178	25361.21970	70.02378	25392.69680	70.05858	25391.47300
9	80.87658	[illegible]	80.00090	[illegible]	80.03603	[illegible]
10	90.88730	[illegible]	90.09318	[illegible]	90.02528	[illegible]
11	100.88475	20252.46610	100.06850	22654.91550	100.00263	24037.06970
12	110.94875	12173.77750	110.00525	17872.51570	110.01300	20168.75960
13	120.06125	5157.45632	120.09925	8425.23684	120.10300	12121.49320
14	130.18650	2391.39480	130.05125	3187.32727	130.02300	4682.51009
15	140.31075	1368.28439	140.12150	1542.76523	140.01725	2116.71258
16	147.34525	1350.11261	148.40000	1347.77439	148.24500	1352.07523
17						
18	DMA completed successfully!					

Fig. 3: Finite Element Model

Fig. 4: Output Parameter

Pilot Project w/ Dynardo

Simulation Task

Parameter Identification

Conclusions

Material Parameters For Calibration

41 input parameters in total: E_0, E_1, ν, C_1, C_2 and α_i (2x18)

Elastic Modulus

$$\begin{aligned} E(T) &= E_0 + E_1 \cdot T \\ E_0 &\dots \text{ constant term} \\ E_1 &\dots \text{ linear term} \end{aligned}$$

Poisson Ratio

$$\nu(T) = const$$

Relaxation Data (Master Curve @ T_0)

$$G(t,T) = G(T) \cdot \left[\alpha_\infty^G + \sum_{i=1}^{18} \alpha_i^G \cdot \exp\left(-\frac{t}{\tau_i}\right)\right]$$

$$K(t,T) = K(T) \cdot \left[\alpha_\infty^K + \sum_{i=1}^{18} \alpha_i^K \cdot \exp\left(-\frac{t}{\tau_i}\right)\right]$$

Time-Temperature Shift Function

$$\ln(a_T) = C_1 \cdot (T - T_0) + C_2 \cdot (T - T_0)^2$$

$$\Delta t_{eff} = \Delta t \cdot \exp(a_T)$$ effective time step

Sensitivity Analysis (1)

Correlation and Coefficient of Determination

Definition design space → Trial and Error, Experience

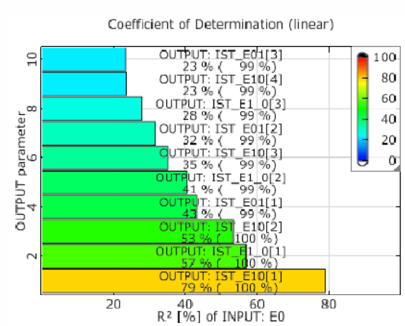
optiSLang creates 100 Latin Hypercube samplings.

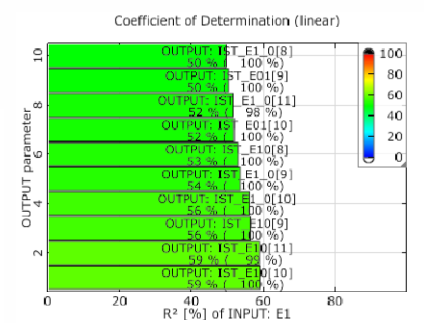
$$\text{Constraint}: \sum_{i=1}^{18} \alpha_i < 1.0$$

Study sensitivity of input parameters on output vector elements.

Sensitivities:

E_0, E_1, C_1	$\rightarrow$	high
C_2, α_i^G	$\rightarrow$	small
ν, α_i^K	$\rightarrow$	none

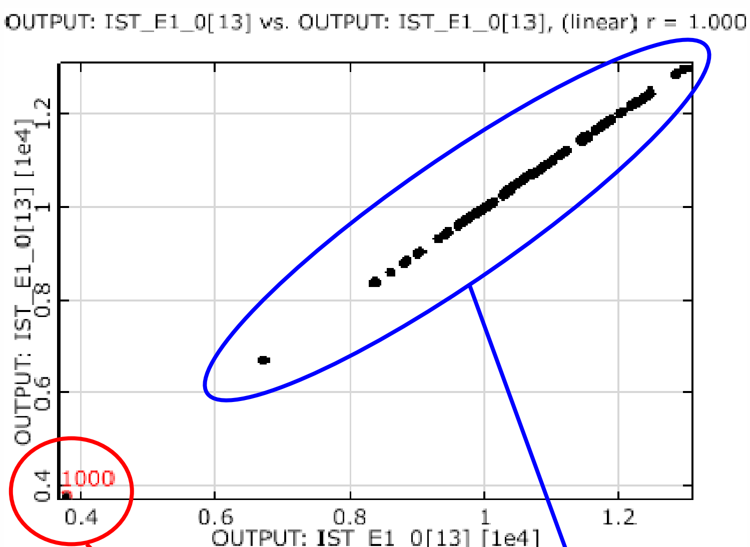


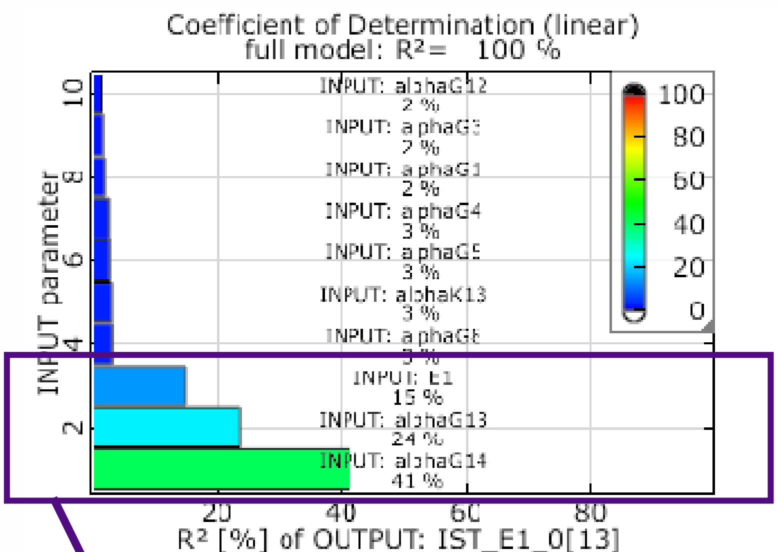


Sensitivity Analysis (2)

Variation Space

Few reference values are outside the variation space of the sensitivity study.





Reference

Variation Space

Variables that have significant effect on particular vector element

Identification (1)

Initialization of Identification Task

Design space for identification has been reduced to 22 variables:

$$\boxed{E_0, E_1, C_1, C_2, \alpha_i^G} \qquad \cancel{\boxed{\nu, \alpha_i^K}}$$

In addition, lower and upper bounds of some variables are adjusted.

⇨ 10 best designs out of LH sampling are used to initialize identification.

Identification (2)

Objective Function and Constraints

Minimize root mean square error of experimental and simulated data.

$$F = \sqrt{\frac{\sum \left(\log\left(E'_{i,Sim}\right) - \log\left(E'_{i,Exp}\right)\right)^2}{i-1}} \rightarrow \min$$

(implemented as user vector routine)

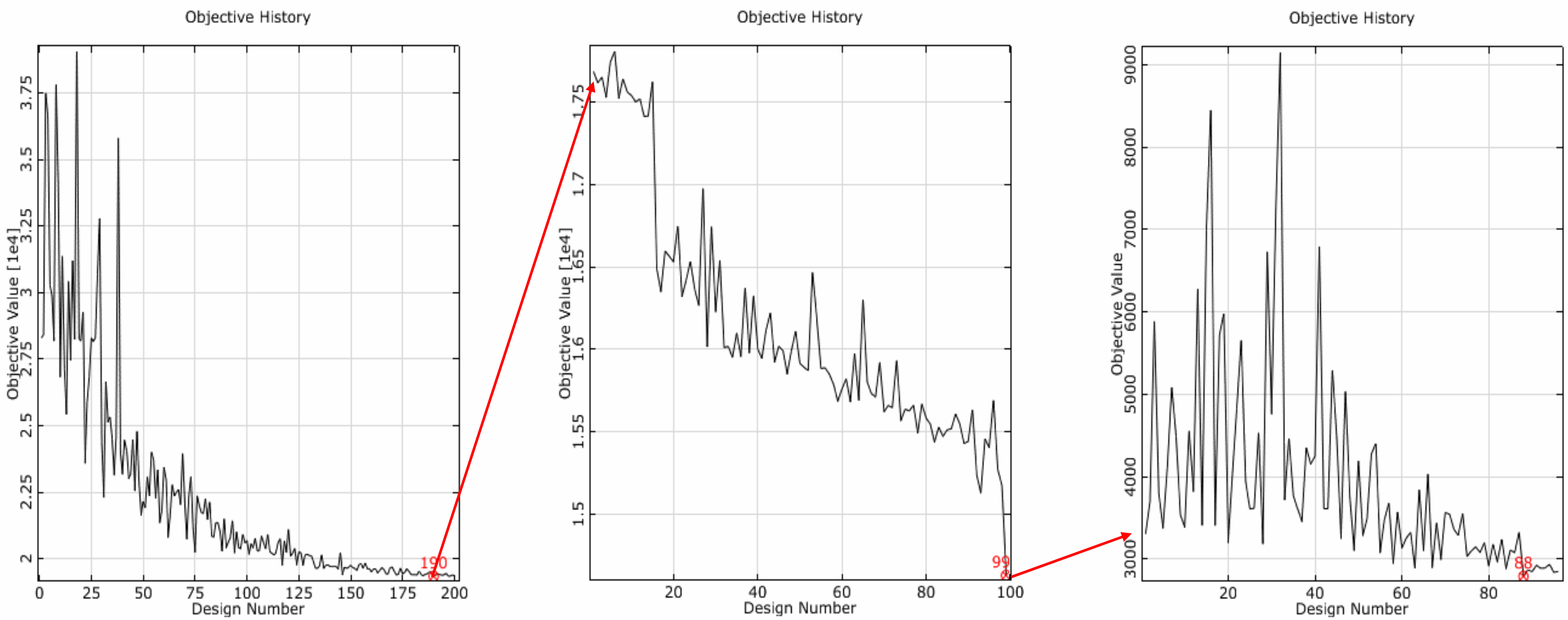
Start w/ global search strategy using optiSLang default settings.

$$\text{Constraint}: \sum_{i=1}^{18} \alpha_i < 1.0$$

! Never analyze non-physical design option of *optiSLang*

Evolution of Identification

Genetic Algorithm | **Evolutionary Run 1** | **Evolutionary Run 6**



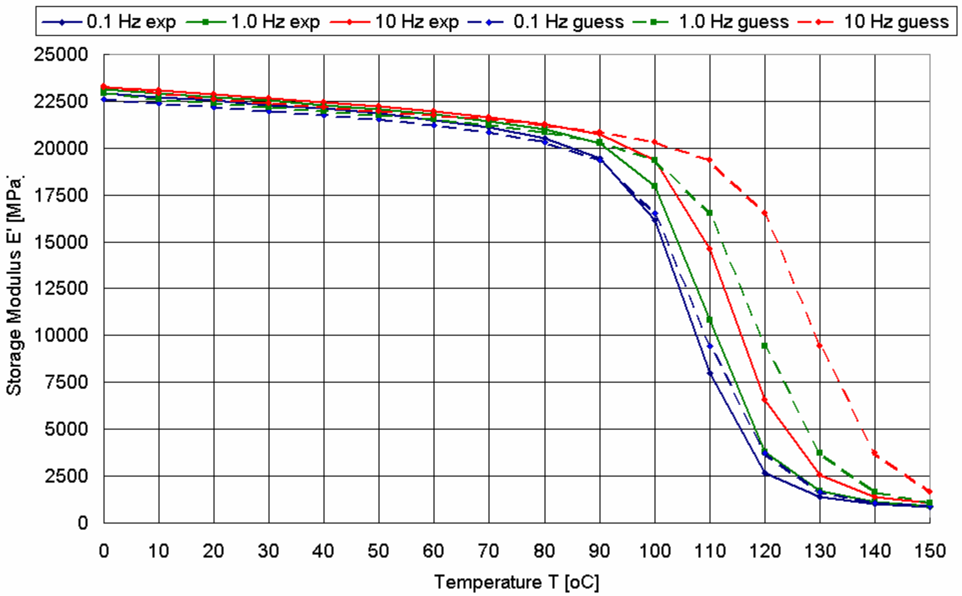
After the global optimization run the solution could be improved about **50 %**!

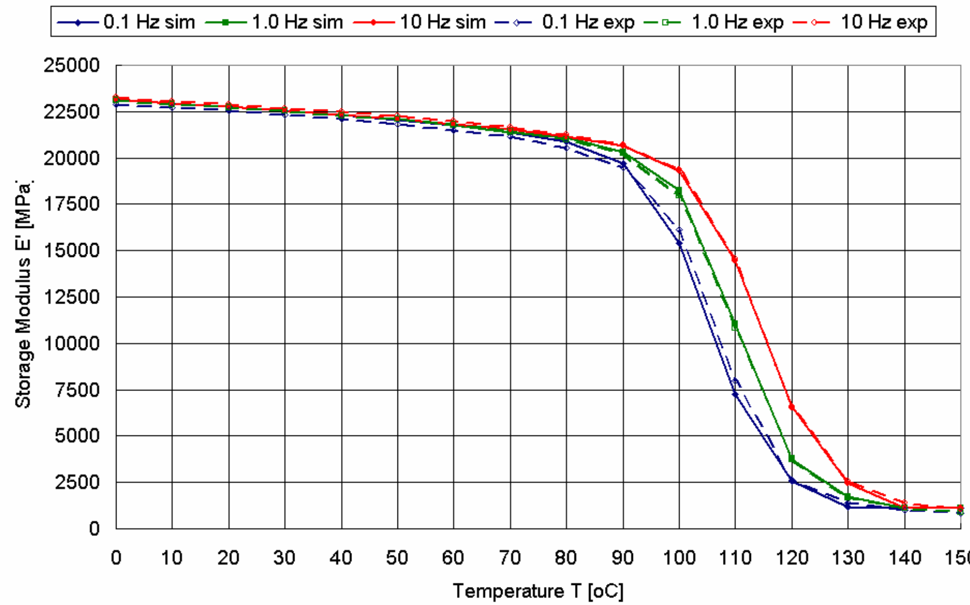
By design improvement strategy the quality of the global solution could be improved significantly.

<u>Final settings:</u>
mutation rate = 0.5
standard deviation < 0.05

Result Parameter Identification

Total Costs of Identification approx. **1000 Solver Calls**.





Initial design using conventional approach (trial and error combined w/ experience).

Best design based on synchronous identification of glass constants, master curve and time-temp. shift function.

Identification Flow For Visco-Elastic Materials

Sensitivity Analysis

only for new material test

Latin Hypercube Sampling w/ 100 samples

➔ remove parameter from the design space that don't show sensitivity on the objective function

Global Optimization

only for new material, e.g. adhesive

Genetic Algorithm w/ population size 10 over 20 generations

➔ search for "global optimum" in design space

Design Improvement

Best method to adjust already available data, e.g. for new filler size

Evolutionary Search w/ 1 parent and 5 newborns over 20 generations

➔ further improvement of the best design from "global optimization"

Local Optimization

not necessarily needed

Gradient based (NLPQL) method

➔ fine tuning of the improved material parameters

Pilot Project w/ Dynardo

Simulation Task

Parameter Identification

Conclusions

Conclusions

- optiSlang has been applied for identification of mold compound constitutive law by calibrating simulation to measurement (Dynamic Mechanical Analysis)
- Sensitivity analysis should be applied first to reduce the dimension of the design space for efficient optimization.
- Genetic Algorithms are efficient to identify parameter sets (master curve data and time-temp. shift function constants) which already characterize the visco-elastic response of the material in first assumption.
- Evolutionary search strategies can be applied very effectively to improve the material data further or to adjust already available data of a similar material, e.g. mold compound w/ different filler content or size.

Thank you

The World's Leading
Creative Memory Company