Optimization and Quick Verification of an Electric Vehicle Side Frame Design using Machine Learning Methods

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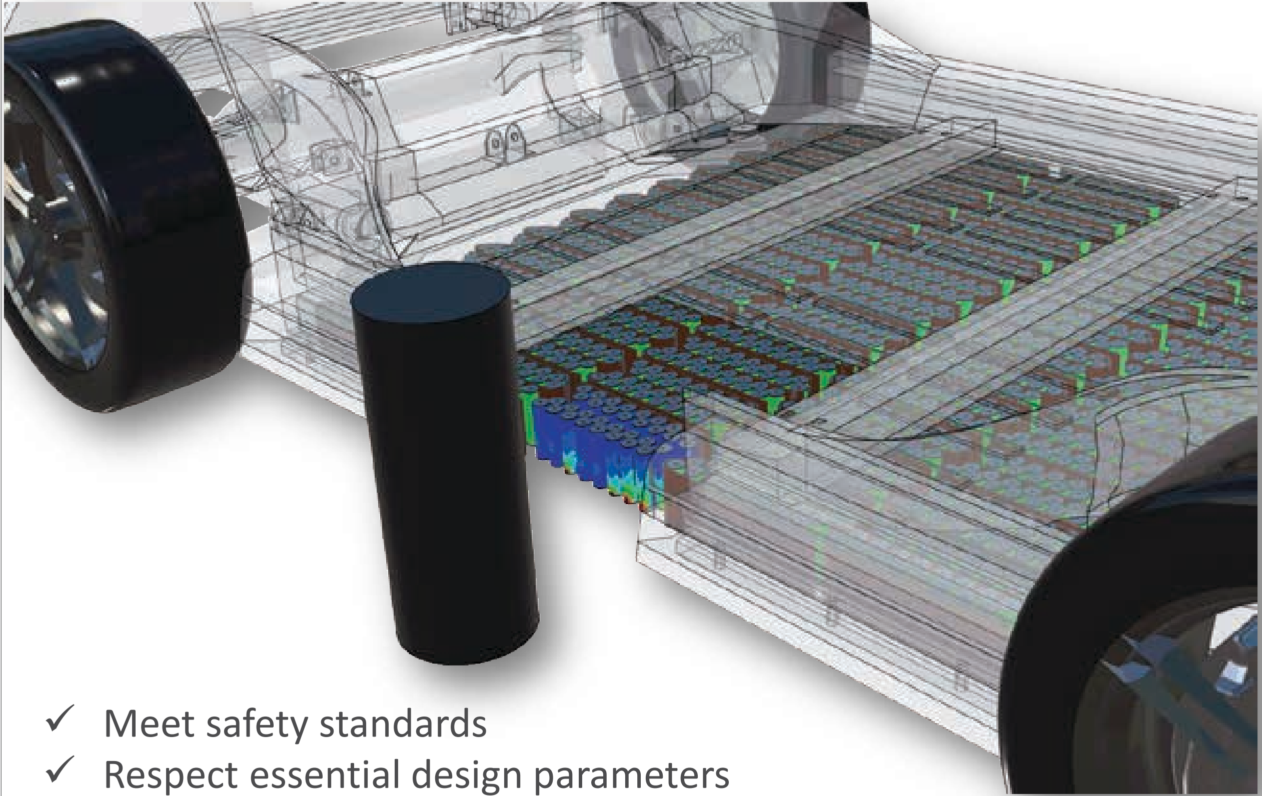
Scope

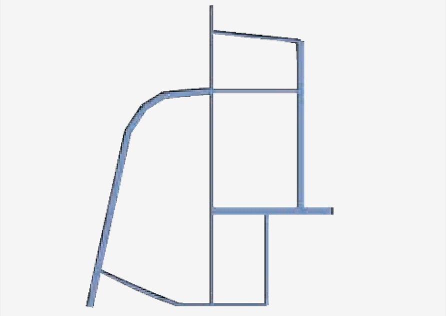


- ✓ Meet safety standards
- ✓ Respect essential design parameters

Initial Rocker Design

ML Optimization

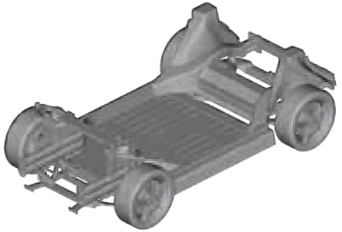
Optimal Design



Why Machine Learning?

Conventional Optimization Methods:

Initial Model



Optimization Set-Up

Analysis

Update FE model

Complete Optimization?

Results Inspection

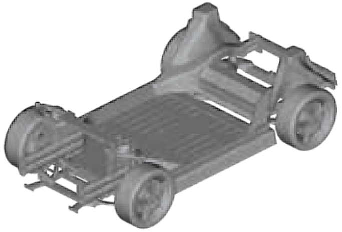
Design cycle iteration

Final Result

Why Machine Learning?

ML Optimization Method:

Initial Model



Generation of Datasets

Design Of Experiments

Predictor Training

Machine Learning

Optimization Set-Up

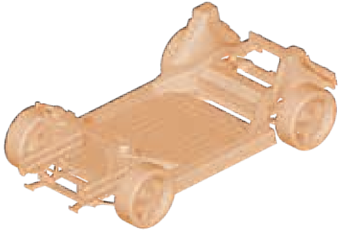
Optimal Solution

- ✓ Multiple types of Design Variables
- ✓ Faster

Why Machine Learning?

Quick Verification:

Modified Model



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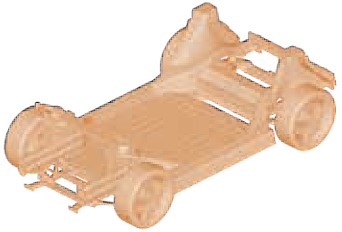
Optimization Set-Up

Optimal Solution

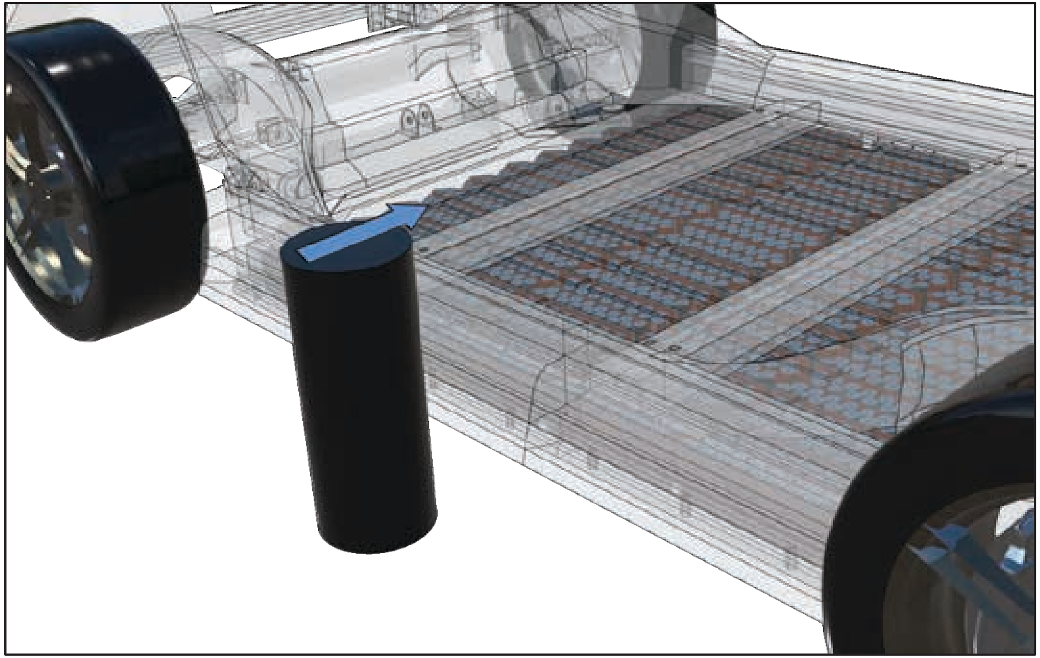
Why Machine Learning?

Quick Verification:

Modified Model



→ **Use of already trained Predictor** + **Similarity factor calculation** → Fast Prediction



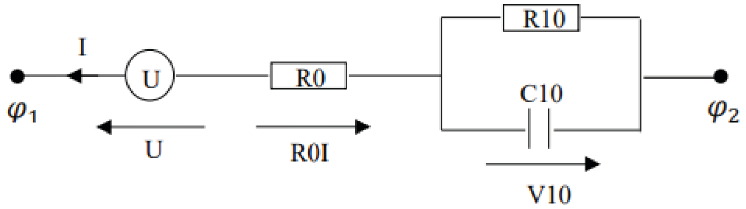
- Model Set-Up
  - EV Platform
  - Rigid Pillar
  - Li-ion Battery packages

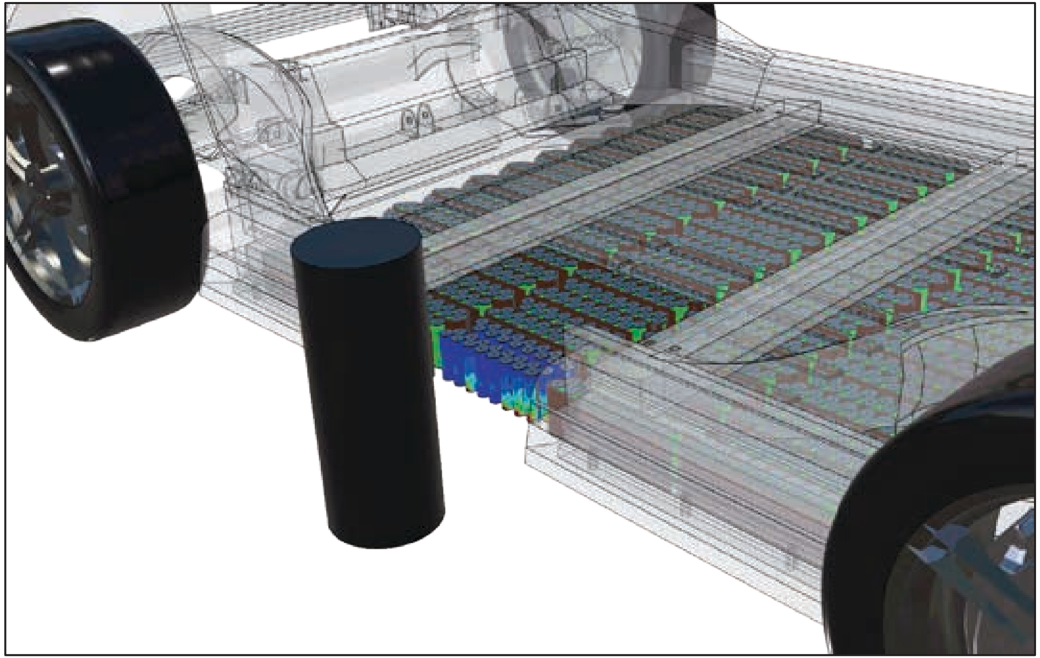
Side Crash Simulation

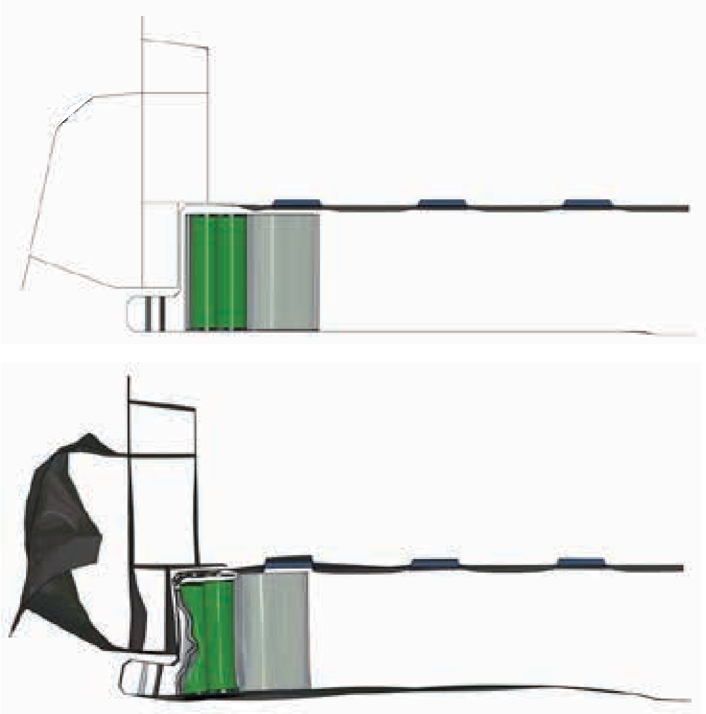
Macroscopic Battery Model:

- Randles equivalent circuit
- Macroscopic [BatMac]
- Homogenized layers

Component	Material
Collector (+)	Al
Cathode	LiFePo4
Separator	PE
Anode	Graphite
Collector (-)	Cu







Objective: Battery Hazard ↘

Constrain: Mass ↘

Randles Short Function

Crash Loads on cells

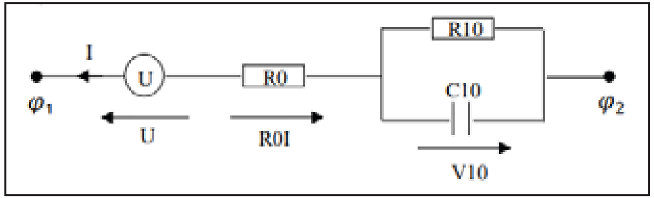
Simulation time step t

Stress $\sigma(t)$

if $\sigma(t) > \sigma_{critical}$

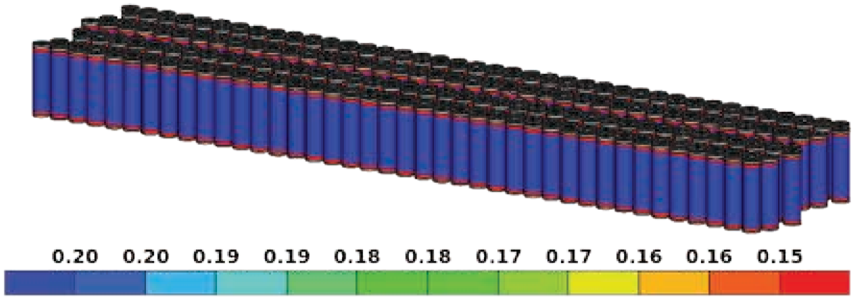
Short Resistance R [Ohm]

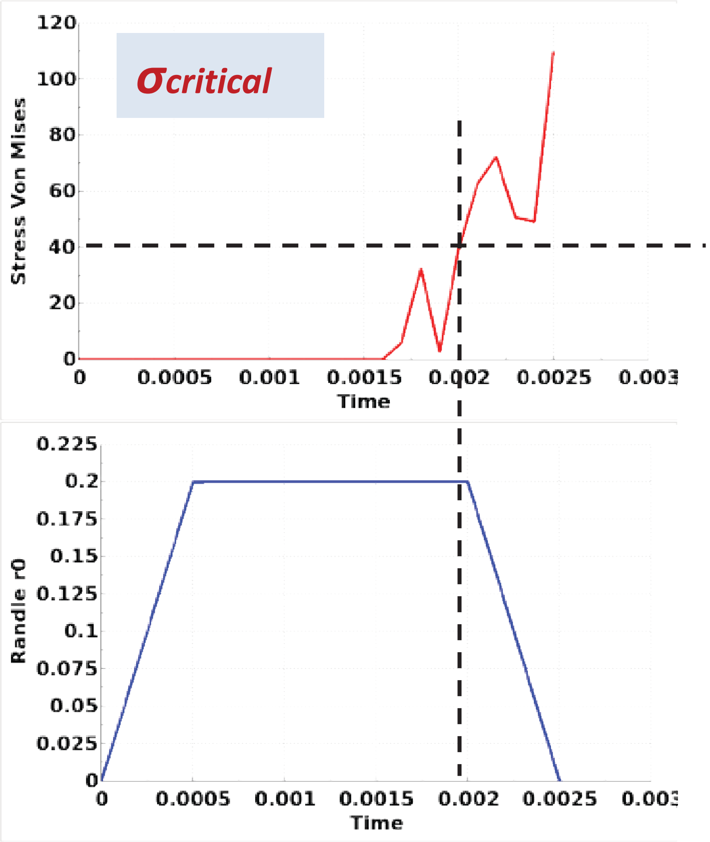
Randles Circuit



To minimize hazard → Retain stress on cell elements below critical value

Randles r0 *[Ohm]*





Randles
R0=0.2 Ohm

→

Internal Short Resistance
R=0.001 Ohm

Optimization Task

Pre-Processing

- ❑ Design Variables
  - Entity Parameters
  - Morph Parameters
- ❑ Output Solver File

Solver

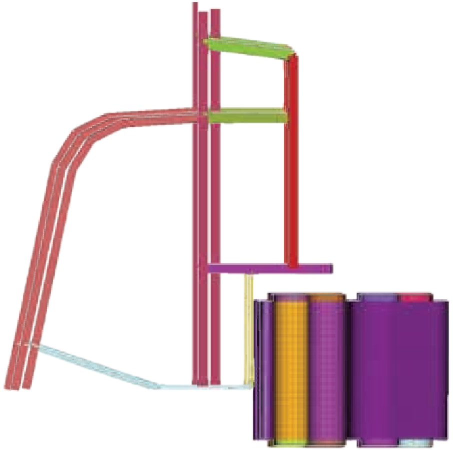
- ❑ FE Analysis

Post-Processing

- ❑ Output Response values

Design Variables:

- Plates Thickness
- Position
- Rocker shape



Response Values:

- Number of Cells where $\sigma(t) > \sigma_{critical}$
- Rocker Mass

Generation of experiments' DV values

Optimization Task

Pre-Processing

- ❑ Design Variables
  - Entity Parameters
  - Morph Parameters
- ❑ Output File

Solver

- ❑ Executable path

Post-Processing

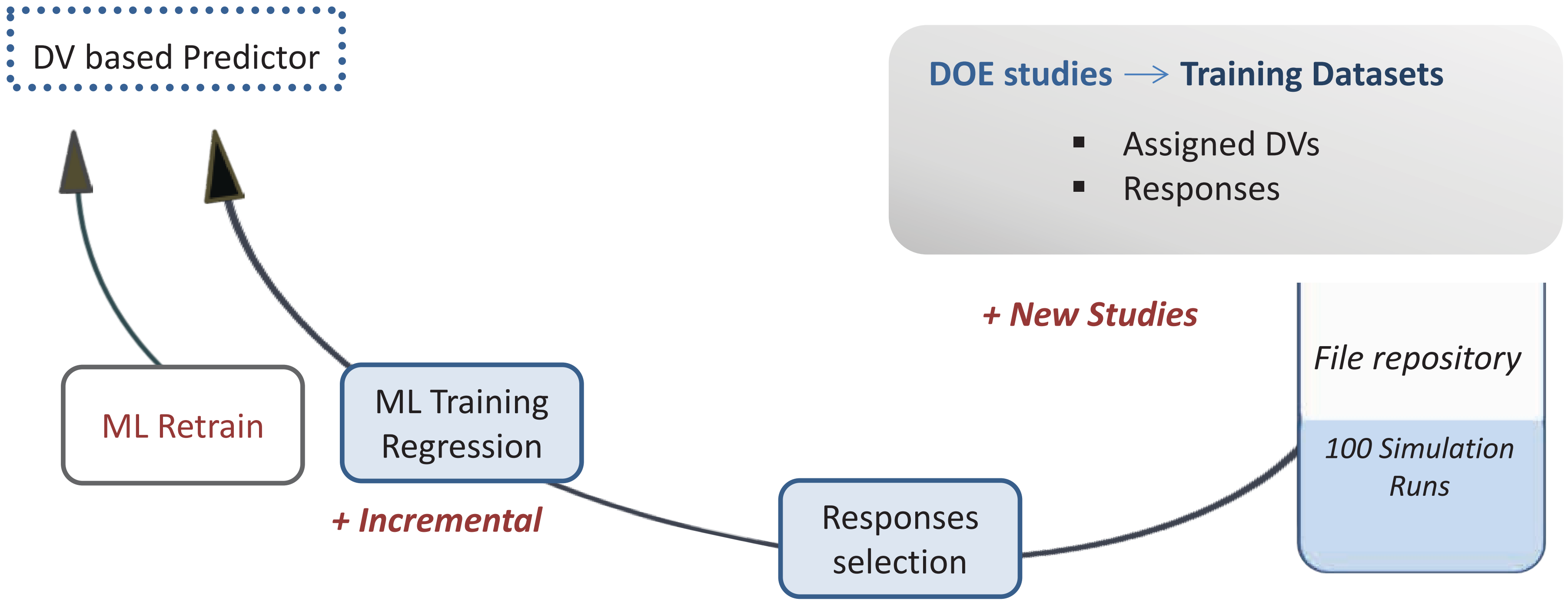
- ❑ Session file - Responses

DOE Set-Up

- Selection of Algorithm
- Selection of DVs
- Number of experiments

File repository

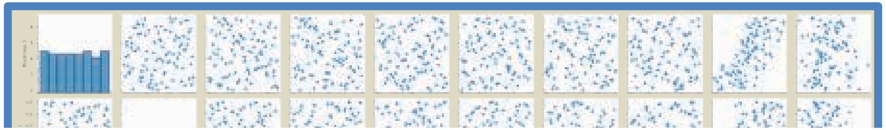
100 Simulation Runs


DV based Predictor
DOE studies → Training Datasets
Assigned DVs
Responses
+ New Studies
File repository
100 Simulation Runs
ML Retrain
ML Training Regression
+ Incremental
Responses selection

- Correlation Matrix of DVs & Responses

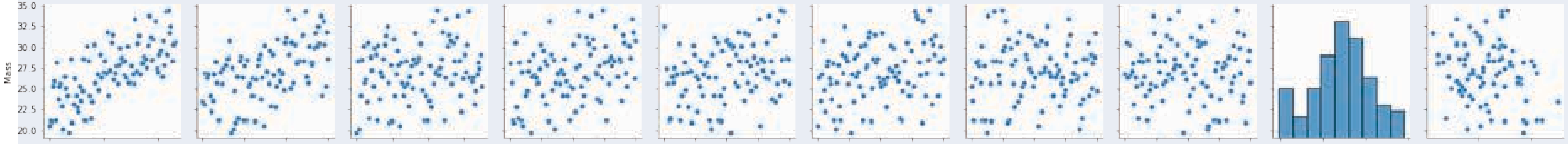
	Thickness 1	Thickness 2	Thickness 5	Thickness 6	Thickness 7	Thickness 8	Plate Location	Pillar Width	Mass	Damaged cells
Thickness 1	1	0.093	-0.022	-0.13	-0.013	0.079	-0.012	-0.095	0.71	0.037
Thickness 2	0.093	1	-0.16	0.082	0.052	0.081	-0.061	0.11	0.53	-0.4
Thickness 5	-0.022	-0.16	1	0.15	-0.015	0.11	0.081	-0.26	0.17	-0.061
Thickness 6	-0.13	0.082	0.15	1	0.28	-0.013	-0.061	0.053	0.37	0.023
Thickness 7	-0.013	0.052	-0.015	0.28	1	0.1	0.0099	0.08	0.29	0.048
Thickness 8	0.079	0.081	0.11	-0.013	0.1	1	-0.013	-0.17	0.28	-0.063
Plate Location	-0.012	-0.061	0.081	-0.061	0.0099	-0.013	1	-0.012	0.02	-0.78
Pillar Width	-0.095	0.11	-0.26	0.053	0.08	-0.17	-0.012	1	-0.026	0.18
Mass	0.71	0.53	0.17	0.37	0.29	0.28	0.02	-0.026	1	-0.2
Damaged cells	0.037	-0.4	-0.061	0.023	0.048	-0.063	-0.78	0.18	-0.2	1

- Responses & Design Variables Pair Plot

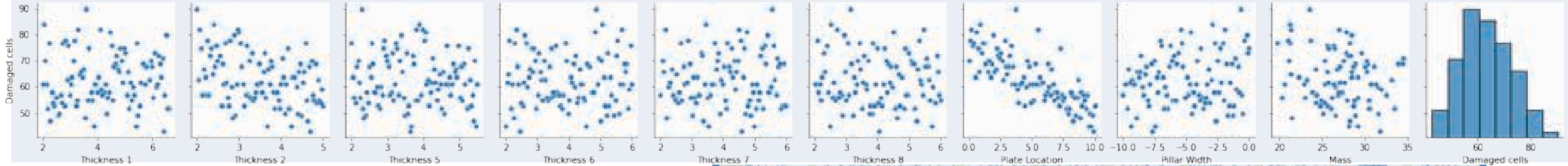


Thickness 1	Thickness 2	Thickness 5	Thickness 6	Thickness 7	Thickness 8	Plate Loc.	Pillar Width	Mass	Damaged cells

Mass

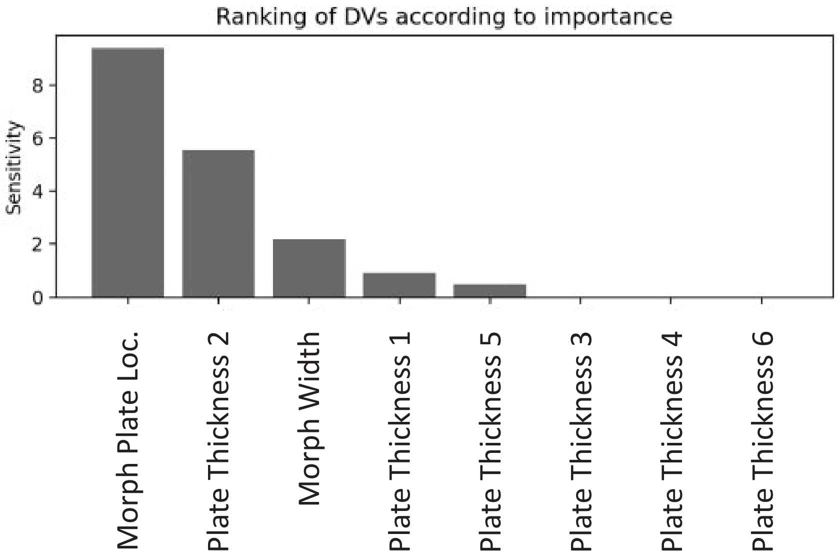


Number of damaged cells

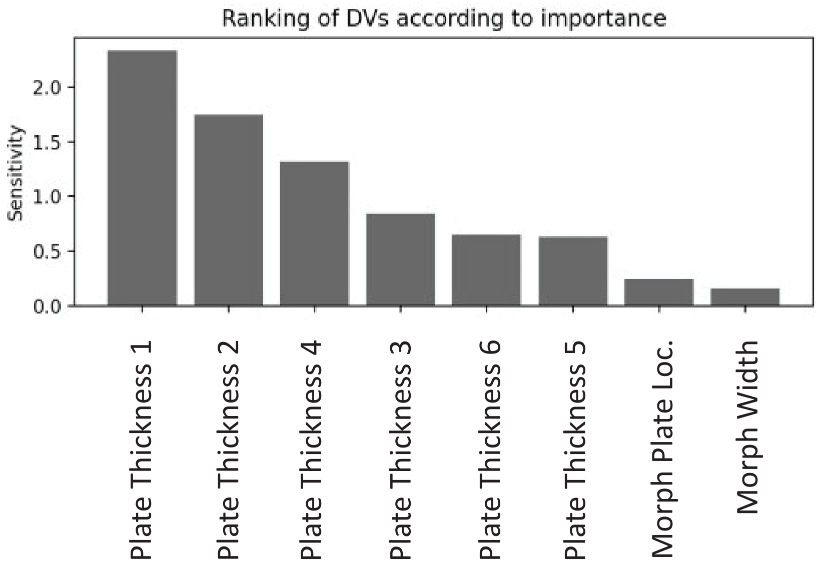


Predictive Power Score: *Mass: 0.98* *Num. of damaged cells: 0.64*

- *Ranking of Design Variables' according to importance*



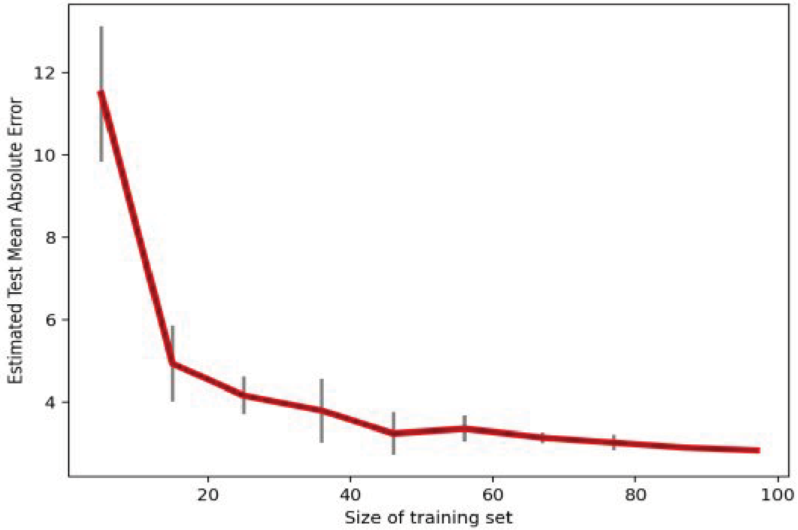
Num. of damaged cells



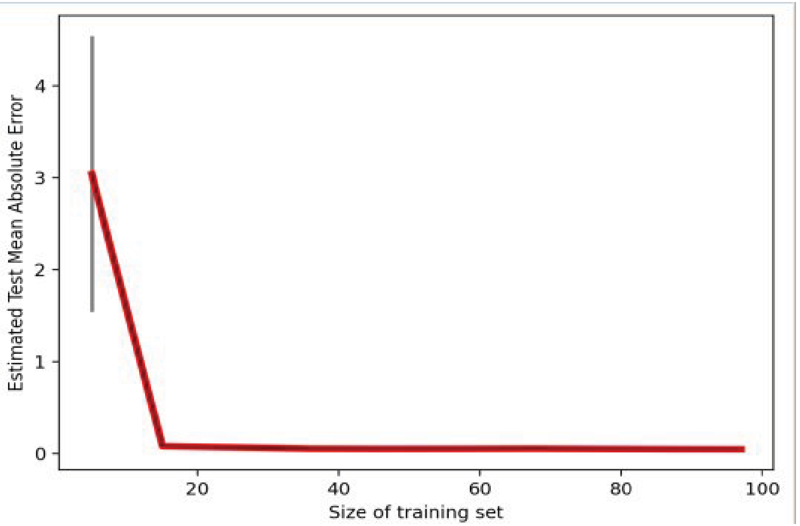
Rocker Mass [kg]

- *Test Accuracy vs. Size of Training Set*

Test Mean Absolute Error estimated using nested cross-validation



Num. of damaged cells



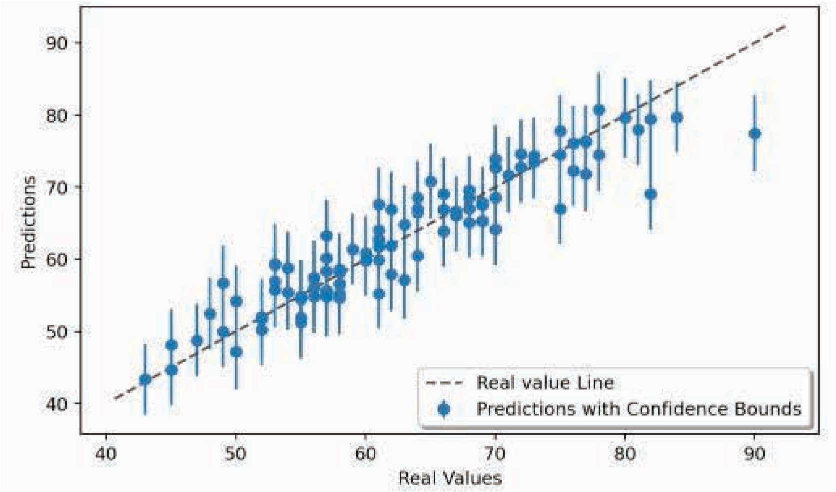
Rocker Mass [kg]

- *Variance Estimation*

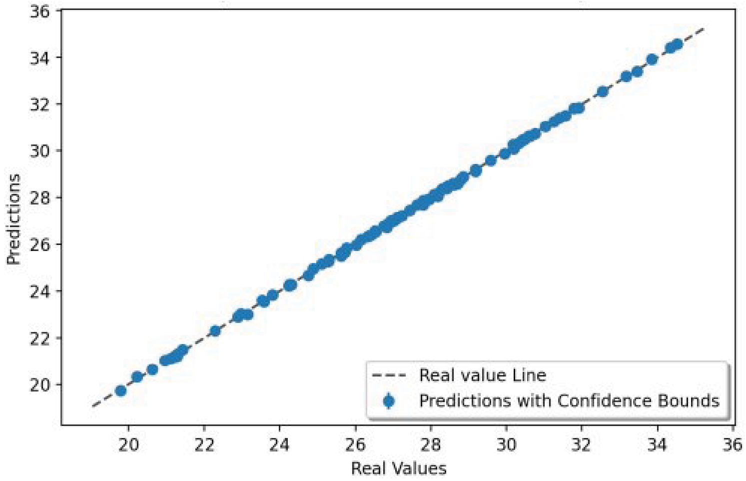
Predictions on a dataset with confidence bounds:

MAE of Variance: 2.9933 Accuracy: 86.735%

MAE of Variance: 0.0459   Accuracy: 87.755



Num. of damaged cells



Rocker Mass [kg]

Parameters

- Algorithm
- Convergence Tolerance
- Iterations

Predictive Models

- Number of damaged cells
- Pillars Mass

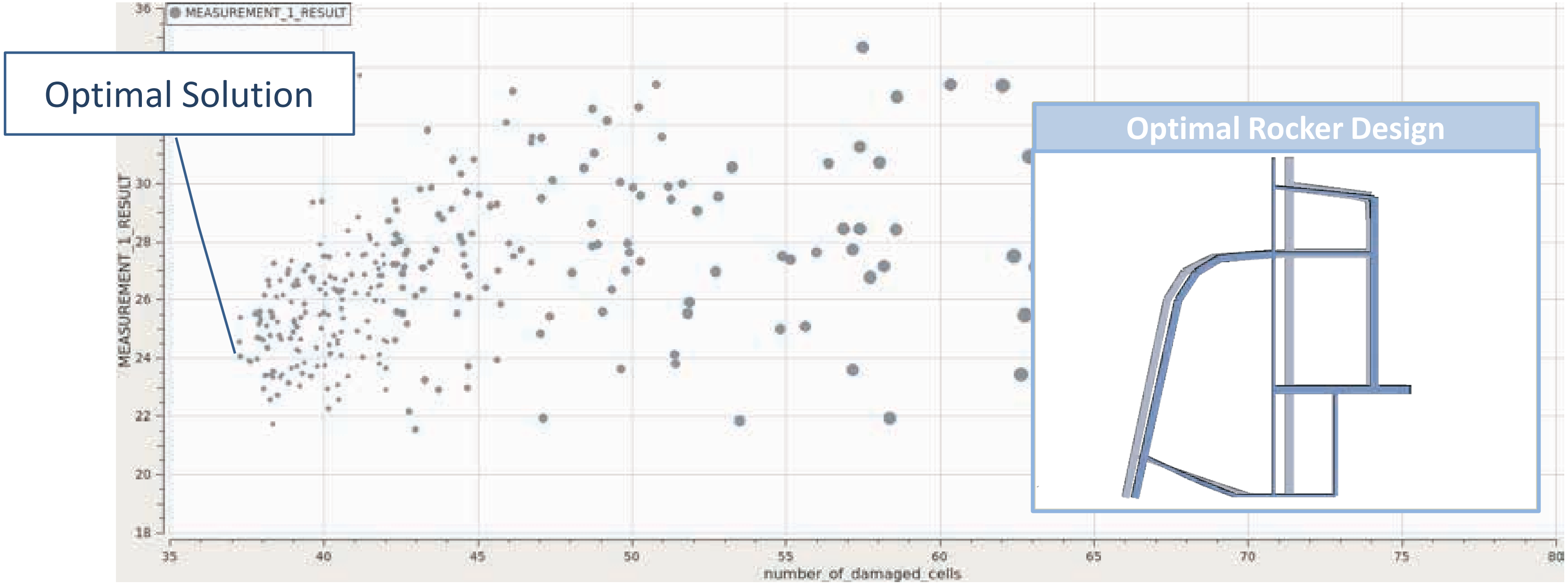
Constrains & Objective

- Mass < 36 kg
- Minimize the number of damaged cells

- Differential Evolution
- 0.0001
- 600

Optimizer output

- Predicted mass: 24.57 kg
- Predicted Num. of damaged battery cells: 37

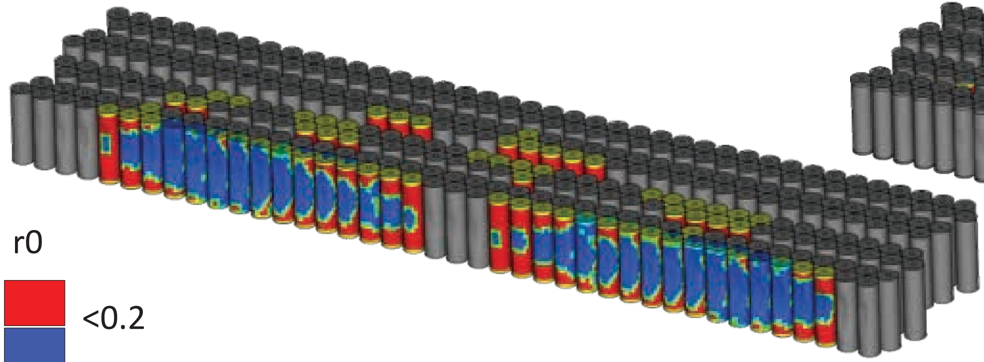


Mass vs. Number of damaged cells

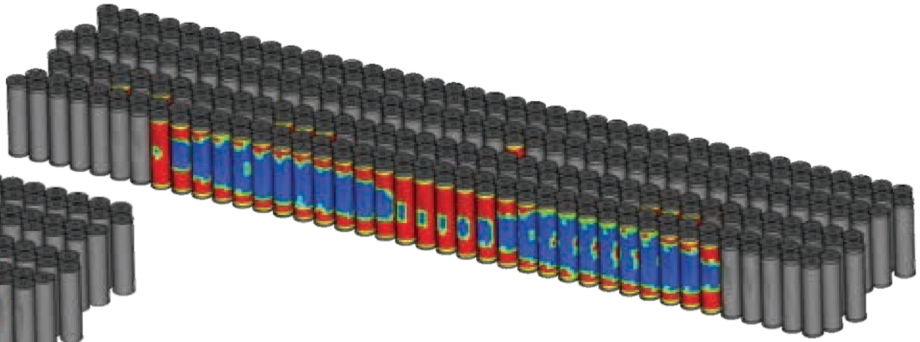
○ Optimization Evaluation

Response	Initial Model	Predicted Optimal	Validated Model
Mass [kg]	37.56	24.57	24.39
Num. of damaged cells	68	37	46

68 damaged cells



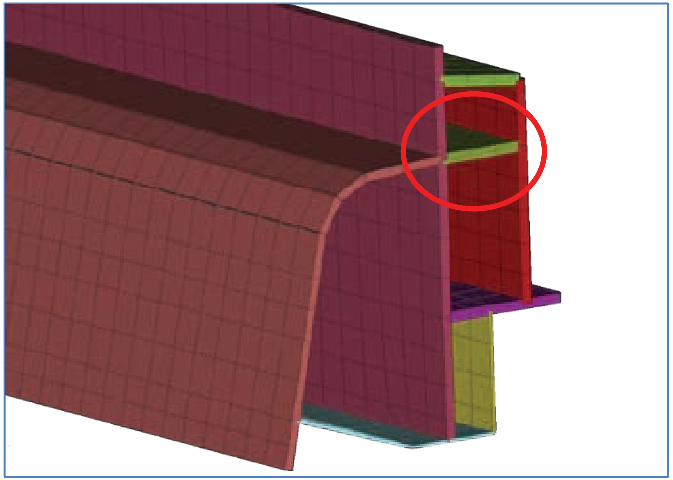
46 damaged cells



r0

<0.2

Baseline Model’s Geometry Modification:



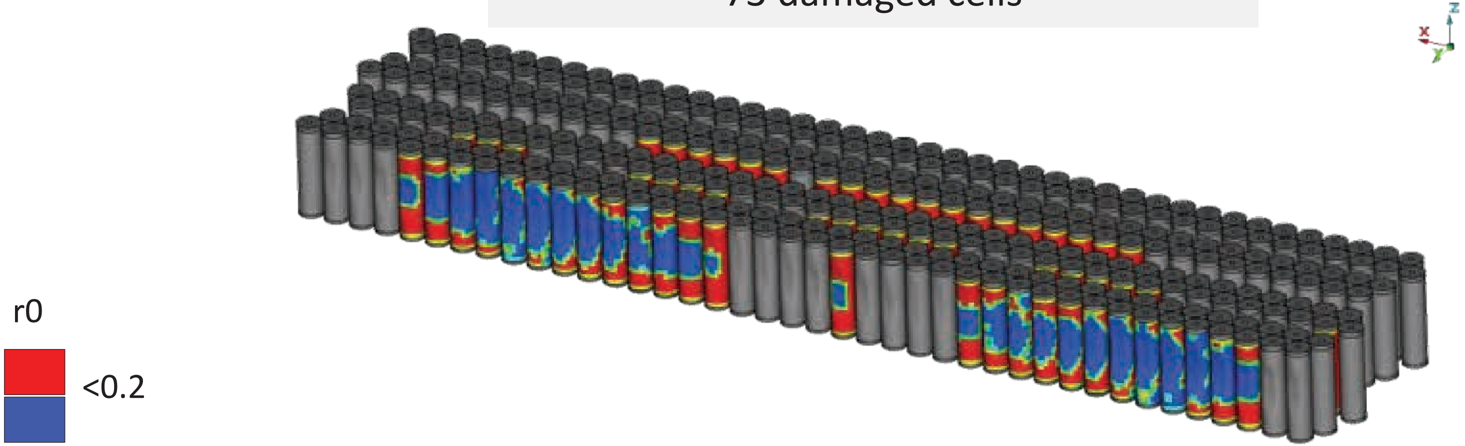
- The previously trained predictive model is used
- A Similarity Factor between the Baseline and Modified Model is calculated per DV

Design Parameter	Similarity Factor (%)
Plate Thickness 1	1.0
Plate Thickness 2	1.0
Plate Thickness 3	1.0
Plate Thickness 4	1.0
Plate Thickness 5	1.0
Plate Thickness 6	1.0

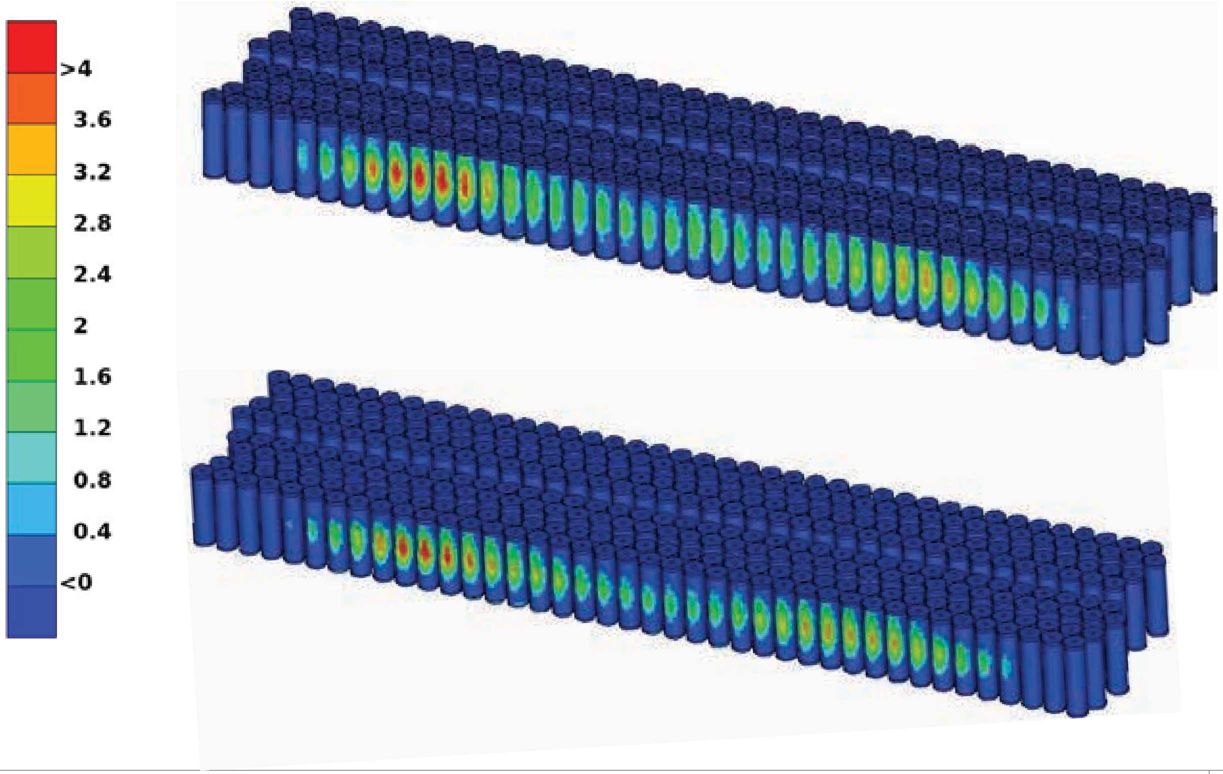
- Modified geometry with Baseline DVs

Response	Initial Model	Predicted	Real Modified
Mass [kg]	37.56	35.8	35.82
Num. of damaged cells	68	72	73

73 damaged cells



- **Same dataset** used to train ***3D-results*** **ML Predictor**



Predicted Displacement

Validated Displacement

- A semi-automated Optimization workflow with Machine Learning methods has been introduced
- The optimal design of an EV side frame is achieved by eliminating li-ion batteries hazard & preserving low mass
- The same predictive model can be used to quickly verify any considerably small modifications of the baseline model
- The procedure is completely customizable at every stage, suitable for any other complex problem

BETA

SIMULATION SOLUTIONS

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