Fulfill range, acceleration and cost targets using battery sizing

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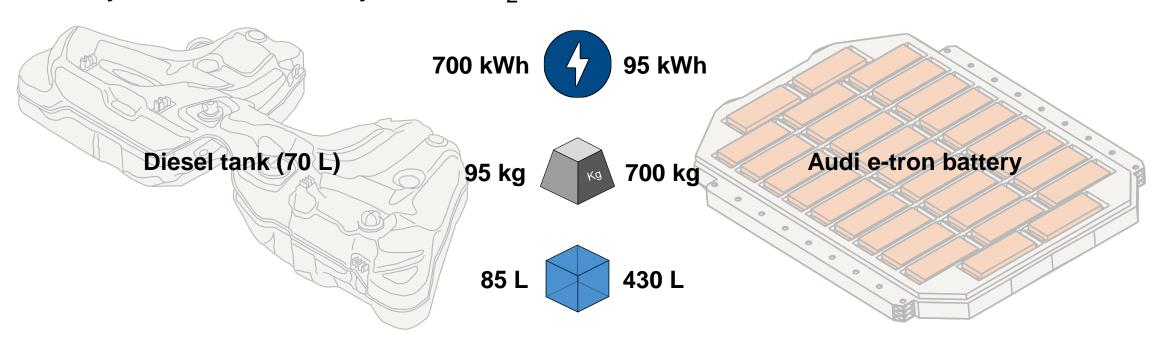


- Problem description
- Modeling of a Battery Electric Vehicle with the Virtual Vehicle Composer
- Parameter sweep
- Numerical optimization of the battery size and additional parameters
- Summary and outlook

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The electrification of the powertrain

- Global effort to reduce human-induced CO₂ emissions
- The automotive sector focuses on reducing the fleet emissions
- Battery Electric Vehicles (BEVs) are a promising long-term solution since they do not cause any local CO₂ emissions

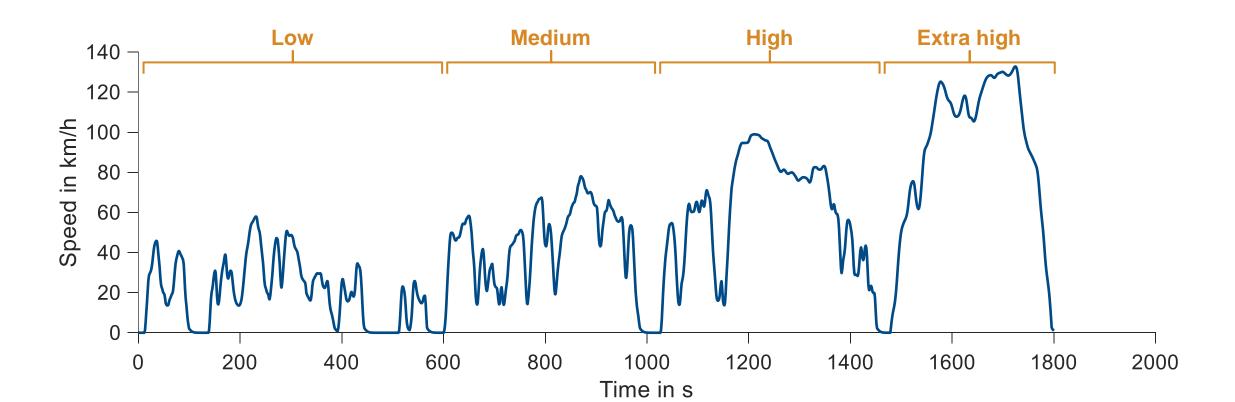


The electrification of the powertrain

- The battery impacts system-level specifications
 - Vehicle mass
 - Energy consumption
 - Vehicle range
- The battery's impact represents a major challenge for BEVs development
- Today's goal is to demonstrate how MathWorks tools support:
 - Configuring and building BEV model for drive cycle / performance analysis
 - Sizing components (such as the battery)
 - Performing component- and system-level optimizations

System-level targets

System-level target	How to evaluate		
Acceleration time t ₀₋₁₀₀ in s	Perform Wide Open Throttle Test (WOT)		



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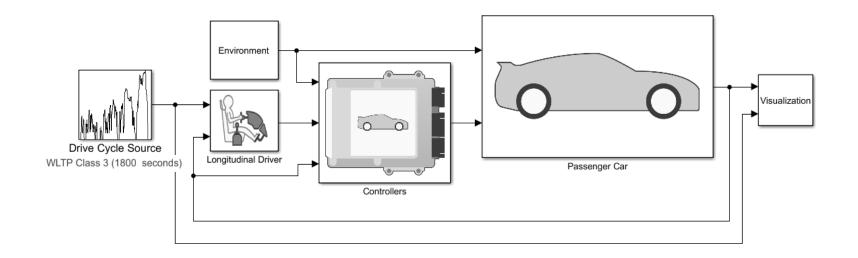
Vehicle modeling for sizing task

Requirements

- Fast vehicle model creation
- Easy adaptability of model including component customization
- Fast model execution for optimization at appropriate fidelity level

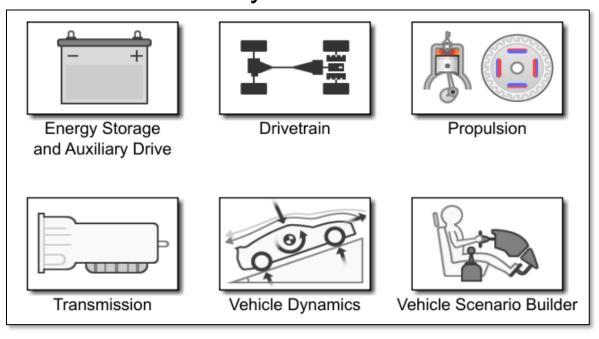
Powertrain Blockset

- Provide starting point for engineers to build plant / controller models
- Provide documented white-box models
- Provide fast-running models that also work with popular HIL systems

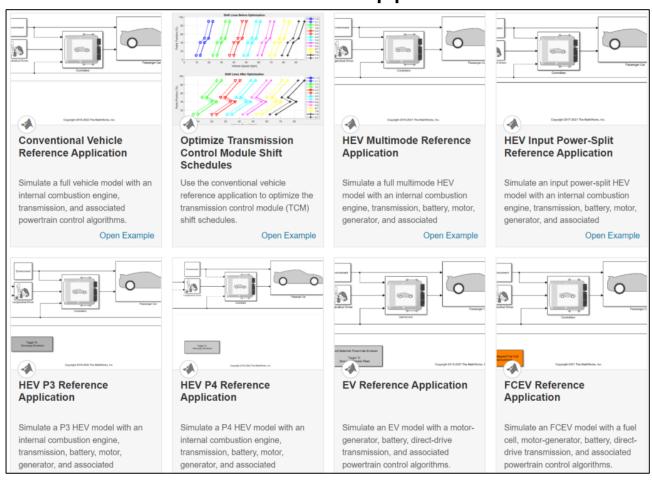


Starting with Powertrain Blockset

Library of blocks



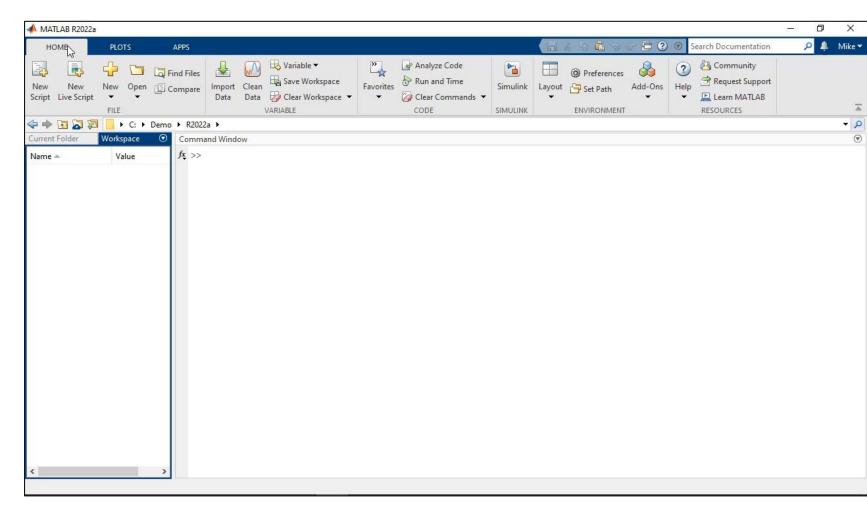
Pre-built reference applications



Virtual Vehicle Composer App

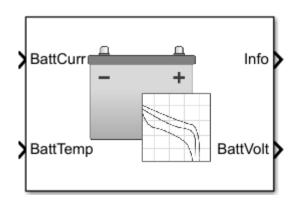
New in R2022a

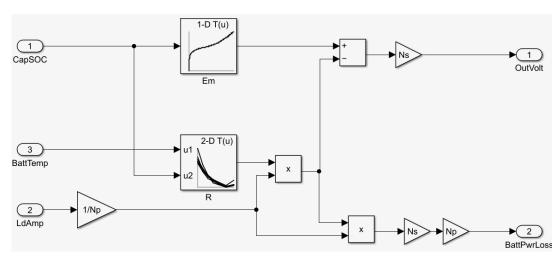
- Unified interface to quickly configure a virtual vehicle model, select test cases and review results
- Available with
 Powertrain Blockset
 and / or Vehicle
 Dynamics Blockset
- Includes detailed powertrain models, vehicle dynamics and closed-loop controls
- Model can be further customized



Battery model

- Datasheet Battery block
 - Simple lumped, but fast model for system-level studies
 - Accounts for changes in Ns and Np
 - Temperature treated as external signal





$$E_{m} = f(SOC)$$

$$R_{int} = f(T, SOC)$$

$$V_{T} = E_{m} + I_{batt}R_{int}$$

$$I_{batt} = \frac{I_{in}}{N_{p}}$$

$$V_{out} = \begin{cases} N_{s}V_{T} & \text{unfiltered} \\ \frac{V_{out}}{\tau s + 1} & \text{filtered} \end{cases}$$

$$SOC = \frac{1}{Cap_{batt}} \int_{0}^{t} I_{batt}dt$$

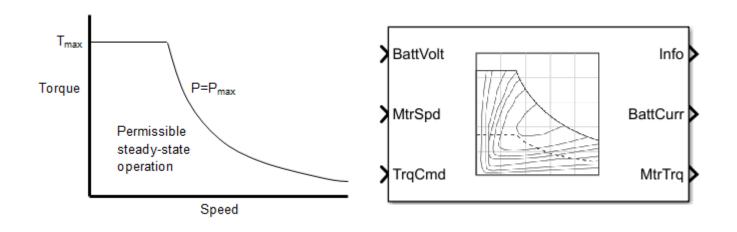
$$Ld_{AmpHr} = \int_{0}^{t} I_{batt}dt$$

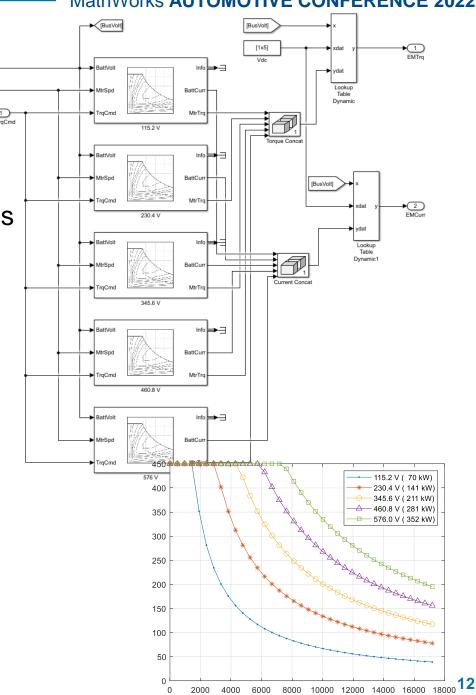
MathWorks **AUTOMOTIVE CONFERENCE 2022**

Motor model

Mapped Motor block

- Simple lumped, but fast model for system-level studies
- Neglects impact of bus voltage (Ns) on base speed
- Used motor maps at 5 bus voltage levels to capture effect of Ns on max motor torque





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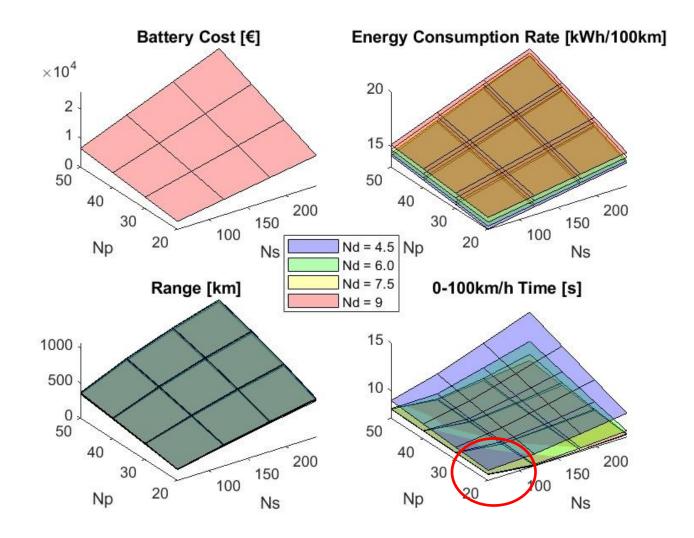
Base vehicle properties (midsize limousine)

Parameters (fixed)	Value	
Vehicle mass (without battery) [kg]	1291	
Wheelbase; Width; Height [m]	2.875; 1.85; 1.44	
C _D (Aerodynamic drag)	0.23	
Front area [m²]	2.4	
Cell voltage [V]	3.6	
Cell capacity [Ah]	4.8	
Battery energy density [Wh/kg]	145	
Battery costs [€/kWh]	125	

Metric	Baseline
Cell configuration (Ns,Np)	96s31p
Gearbox ratio (Nd)	9.0
Range [km]	340
Energy consumption [kWh/100km]	15.1
Battery cost [€]	6428
Acceleration time t ₀₋₁₀₀ [s]	7.14

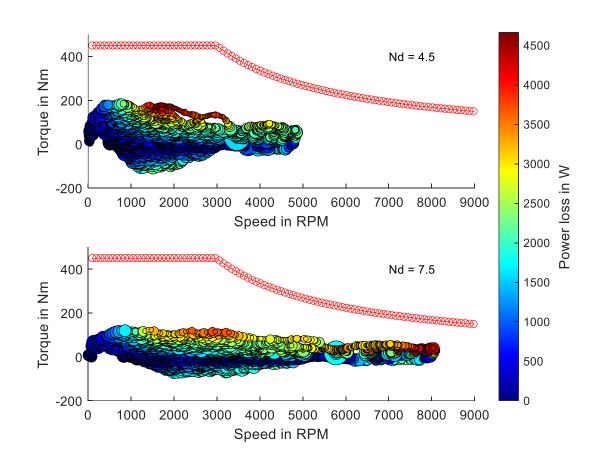
Initial assessment

- Performed initial parametric study
 - Sweep of Np, Ns and Nd
 - Study problem statement before launching long optimization study
- Lessons learned
 - High gearbox ratio (Nd) → better acceleration time but worse energy consumption
 - Higher number of cells → higher range but worse energy consumption



Initial assessment

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 - High gearbox ratio (Nd) → better acceleration time but worse energy consumption
 - Higher number of cells → higher range but worse energy consumption
 - WLTP never pushed motor to max torque / power limits



Design trade-offs

	Metric improves as			
Metric	Ns	Np	Nd	
Mass	▼ (fewer cells)	▼ (fewer cells)		
Energy consumption	▲ (max torque up to higher speed)▼ (less mass)	▲ (lower resistance)▼ (less mass)	▼ (more efficiency)	
Cost	▼ (fewer cells)	▼ (fewer cells)		
Range	▲ (more energy)▼ (less mass)	▲ (more energy)▼ (less mass)		
Acceleration	▲ (max torque up to higher speed)▼ (less mass)	▼ (less mass)	▲ (more wheel torque)	

Numerical optimization provides a rigorous method to balance competing objectives

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Component sizing problem statement

Goals:

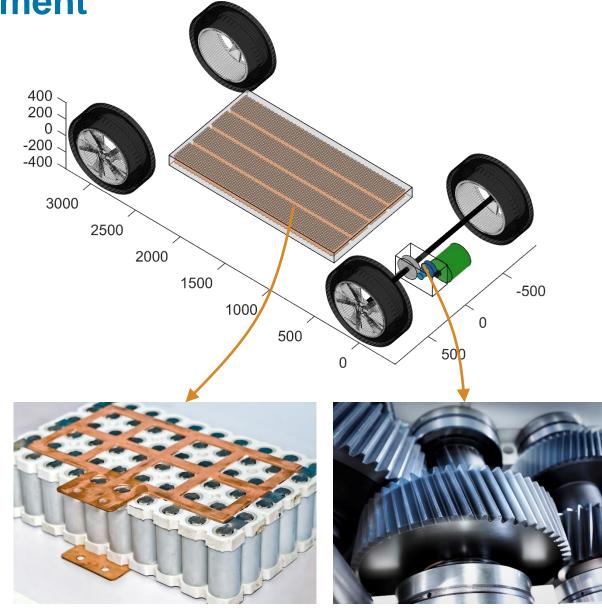
 Find battery size & gearing that provides good efficiency at a reasonable price

Constraints:

- Meets typical driving demands
- Reasonable BEV range
- Reasonable acceleration

Design Variables:

- Number of battery cells in parallel (Np)
- Number of battery cells in series (Ns)
- Gearbox ratio (Nd)



Component sizing problem statement

Goals:

$$min f(\mathbf{x}) = w_1^*ECR + w_2^*Cost$$

ECR = Energy Consumption Rate [Wh/km]

Constraints:

 g_1 : DriveCycleFault ≤ 0

 g_2 : Range \geq 400 km

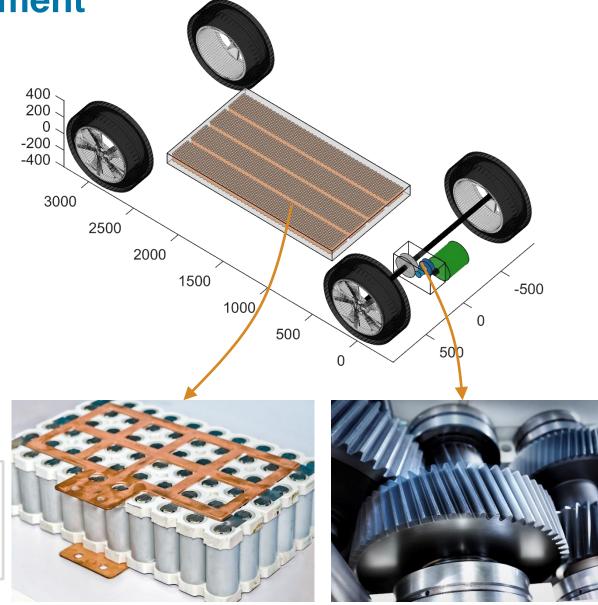
 g_3 : $t_{0-100} \le 8$ sec

Design Variables:

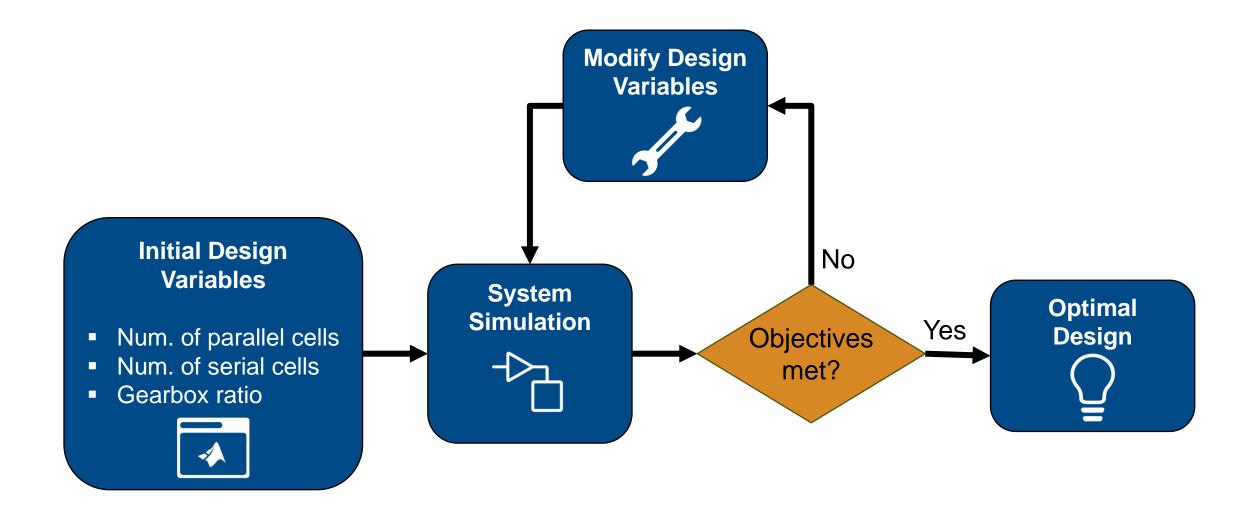
 x_1 : 20 \leq Np \leq 50 (Integer)

 x_2 : 320V /3.6V \leq Ns \leq 600V /3.6V (Integer)

 x_3 : $2 \le Nd \le 10$ (Continuous)



Optimization workflow



Running simulations as a function call

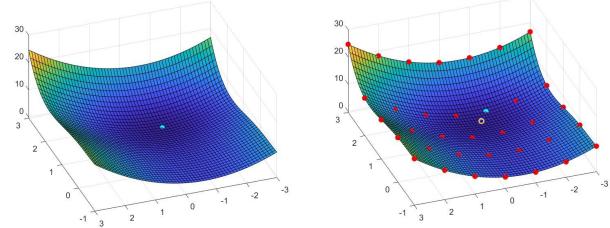
59

end

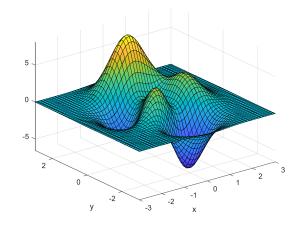
```
Stop Time
                                                                                                                                                                                   function [f, g, ECR, cost] = RunEV(Np, Ns, Ndiff, model)
       % RunEV runs a series of EV sims for a given set of parameters
2
                                                                                                                                                                                   Run
3
                                                                                                                                                            Fast Restart
4
       % Do some internal calculations
                                                                                                                                                                          SIMULATE
       batt_energy = (4.8*Np)*(3.6*Ns)/1000; % 4.8 Ah/string, 3.6 V/cell
       mass = 1250 + batt energy/145*1000; % 145 Wh/kg
       cost = 125 * batt energy; % assume cell cost of $125/kW.hr
8
                                                                                                                                           Info
9
       % Create Simulation Input object to store temporary parameter overrides
                                                  % Run 0-100 kph test
       in = Simulink.SimulationInput(mode] 31
10
                                                                                                                   VelFdbk
                                                 in = in.setVariable('DCidx', 2);
       in = in.setVariable('PlntVehMass', 32
11
       in = in.setVariable('PlntBattNumCel 33
                                                 in = in.setModelParameter('StopTime','20');
12
                                                                                                                                         RefSpc
       in = in.setVariable('PlntBattNumCel 34
                                                  simout = sim(in)
13
                                                                                                                                                                                   LngRef
       in = in.setVariable('PlntDiffrntlRa 35
14
15
                                                 % Post-process WOT result
                                          36
                                                                                                                          Drive Cycle Source
       % Run WLTP drive cycle
16
                                          37
                                                 logsout = simout.get('logsout');
                                                                                                                     WLTP Class 3 (1800 seconds)
17
       in = in.setVariable('DCidx', 1);
                                                 v = logsout.get('Vehicle Speed [m/s]').Values;
                                          38
18
       in - in.setModelParameter('StopTime
                                         39 🗀
                                                  try
19
       simout = sim(in);
                                                      id = find(v.Data>0.1,1,'first');
                                          40
20
                                                      t0 = interp1(v.Data(id-1:id), v.Time(id-1:id), 0.1);
                                          41
21
      % Post-process WLTP result
                                                      id = find(v.Data>27.778,1,'first');
22
       logsout = simout.get('logsout');
                                                      t100 = interp1(v.Data(id-1:id), v.Time(id-1:id), 27.778);
       DCerror = logsout.get('DCFaultTime
23
                                                      t0\ 100 = t100 - t0;
       DCfail = logsout.get('DCFail').Valu
24
                                                  catch
       bp = logsout.get('Battery Power [W]
25
                                                      t0 100 = 100;
       v = logsout.get('Vehicle Speed [m/s 46
26
                                                                                                                                WOT
                                                  end
      % Energy consumption rate in [W.hr/ 47]
27
       ECR = trapz(bp.Time,bp.Data)/3600/(48)
28
                                                 % Assemble results into objective and constraint values
       range = batt energy / ECR * 1000; % 49
                                                 f=[]; g = struct();
                                          50
                                          51
                                                 w = [0.5, 0.5]; % relative weights for the objectives
                                          52
                                                 s = [150, 6250]; % scale factor to normalize objective terms
                                          53
                                                 f = ECR*w(1)/s(1) + cost*w(2)/s(2);
                                          54
                                                 g.DCerror = DCerror*DCfail; % total drive cycle fault time (or 0 if passed)
                                          55
                                          56
                                                 g.range = 300 - range; % range > 300 km
                                          57
                                                 g.t100 = t0 100 - 8.0; % t0 100 < 8.0 sec
                                          58
```

Selecting the appropriate optimization algorithm

- Design Variable Space
 - Continuous
 - Integer (discrete)
 - Mixed Integer
- Local / global optimization task
 - Optimization Toolbox (local)
 - Functions for finding parameters that minimize or maximize objectives while satisfying constraints
 - Global Optimization Toolbox
 - Functions that search for global solutions to problems that contain multiple maxima or minima on smooth or nonsmooth problems
- Problems
 - Linear / quadratic / cone programming
 - Least-squares and nonlinear equations
 - Multiobjective optimization
 - Nonlinear optimization
 - Surrogate, Genetic Algorithm, ...



Objective with single minimum



Objective with multiple minima

Solve expensive nonlinear problems with surrogateopt

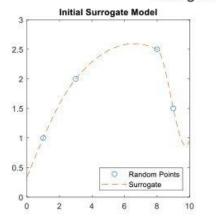
Concept

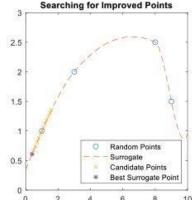
- Create a surrogate model of the objective / constraints
- Find the best point on the surrogate model, then sample new points
 - near the best point found so far (refine solution)
 - far from any sample (improve model accuracy)

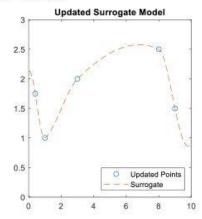
Benefits

- Automatically builds a cheap-to-evaluate surrogate model
- Searches for global solution
- Works in continuous or integer design variables
- Accepts nonlinear, linear, and integer constraints

Using Interpolation to Build a Surrogate Model







Description

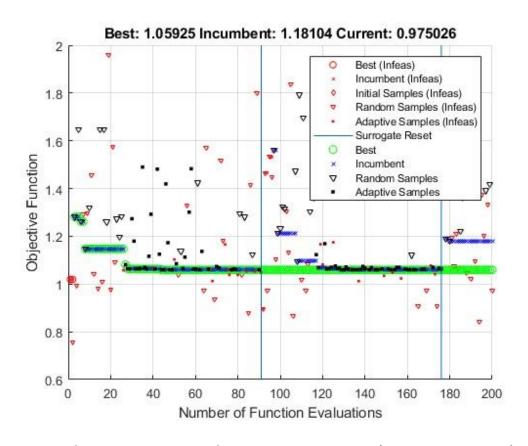
surrogateopt is a global solver for time-consuming objective functions.

surrogateopt attempts to solve problems of the form

$$\min_{x} f(x) \text{ such that } \begin{cases} \text{lb} \le x \le \text{ub} \\ A \cdot x \le b \\ \text{Aeq} \cdot x = \text{beq} \\ c(x) \le 0 \\ x_i \text{ integer, } i \in \text{intcon.} \end{cases}$$

Optimization Results

Metric	Baseline	Target	Optimized (% improvement)
Energy consumption [kWh/100km]	15.1	< 15	14.4 (-4.6%)
Cost [€]	6428	< 7500	7232 (+12.5%)
Range [km]	340	> 400	401 (+17.6%)
Acceleration time t ₀₋₁₀₀ [s]	7.14	< 8	8.0 (+12.0%)
Gearbox ratio Nd	9		5.05
Cell configuration	96s31p		108s31p
Bus voltage [V]	345.6		388.8
Capacity [kWh]	51.4		57.9



Performed 200 function calls (~2,5 hours)

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Summary

- Key take-away:
 - Simulink Virtual Vehicle Composer with Global Optimization Toolbox are rigorous means to identify optimal design parameter configurations
- Topics discussed:
 - BEV model with Virtual Vehicle Composer
 - Apply BEV model to estimate:
 - Acceleration time in s
 - Energy consumption in Wh/km
 - Range in km
 - Battery costs in €
 - Parameter sweep to understand interdependencies and trade-offs
 - Optimize using Surrogate Optimization from the Global Optimization Toolbox

Outlook

- The Virtual Vehicle Composer offers different powertrain architectures
 - Battery Electric Vehicles
 - Internal Combustion Vehicles
 - Hybrid Electric Vehicles
- The virtual vehicle model can be easily modified/extended
- Optimization at component- and system-level
- Wide range of alternatives for optimization algorithms
- For a deeper focus on the battery, we advise Simscape Battery

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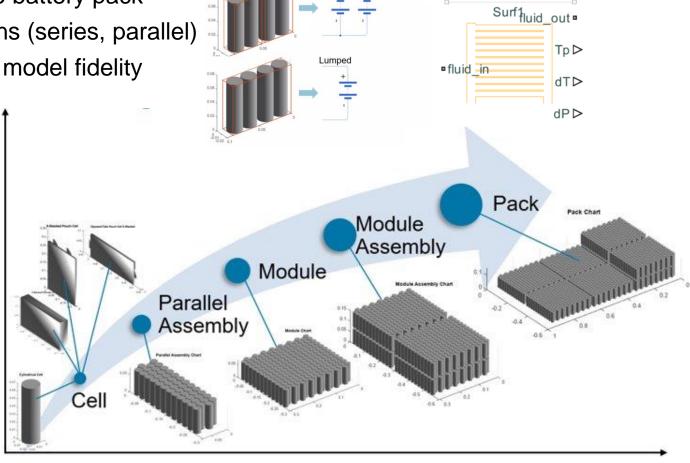
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Next steps: Modeling battery packs with Simscape Battery

Key Features

- Battery Pack Builder (MATLAB API)
 - Automatically assemble cell models into battery pack
 - Define electrical and thermal connections (series, parallel)
 - Adjust tradeoff of simulation speed and model fidelity
- Cooling plate models
 - Parallel channel
 - U-shaped channel
- Battery management algorithms
 - Charge/discharge cycles
 - SOC, SOH estimators
 - Cell balancing, thermal management
- Support for C-code generation
- Application-specific examples
 - EV charging, Microgrid with BESS



Q&A

