Optimizing Calibration Values of Electrified Powertrains with Machine Learning

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Ford Motor Company

Outline

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2. Calibration Optimization Workflow
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   2.2 Development of Customized/Intermediate Algorithms
   2.3 Finding Computing Resources to Run Parallel Simulations
   2.4 Data Analytics and Deployment to Internal Partners
   2.5 System Level Integration of all Components with MBCO Ecosystem

3. Sample Study Results

4. Next Step/Challenges

1. Introduction

Challenge

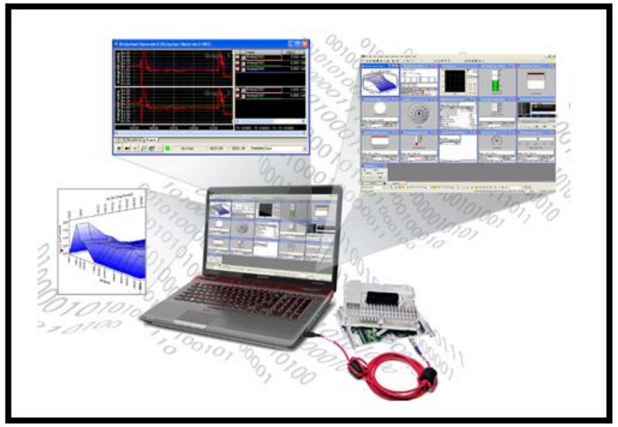
- Calibration of hybrid electric vehicles (electrified powertrains) is a challenging task
- Complexity of the task is increased
  - Scale (large number of calibration constants)
  - Interdependency of these calibration constants
  - Calibrating to cater multiple competing attributes
  - Different regulatory requirements
  - Multiple vehicle programs and different variations of each program
- This attempt requires
  - Many prototypes
  - Engineering + lab time
  - Substantial cost
- Could we use new AI/ML techniques to mathematically optimize calibration constants for complex electro-mechanical systems?

Goals of MBCO Studies

- **Math-based framework for cal. development**
- **Better understanding of system behavior**
- **Reduce**
  - **Engineering time**
  - **Tools needed**
  - **Prototypes**
  - **Testing time**

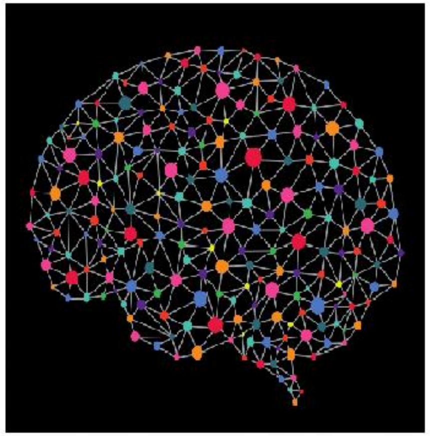
Calibration Engineers

Calibration Tools



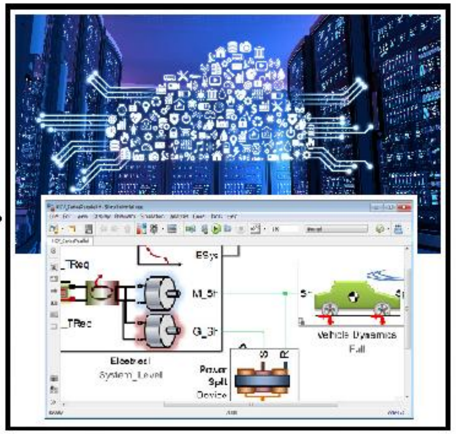
Prototypes + Test Lab

Machine Learning



Intermediate Algorithms

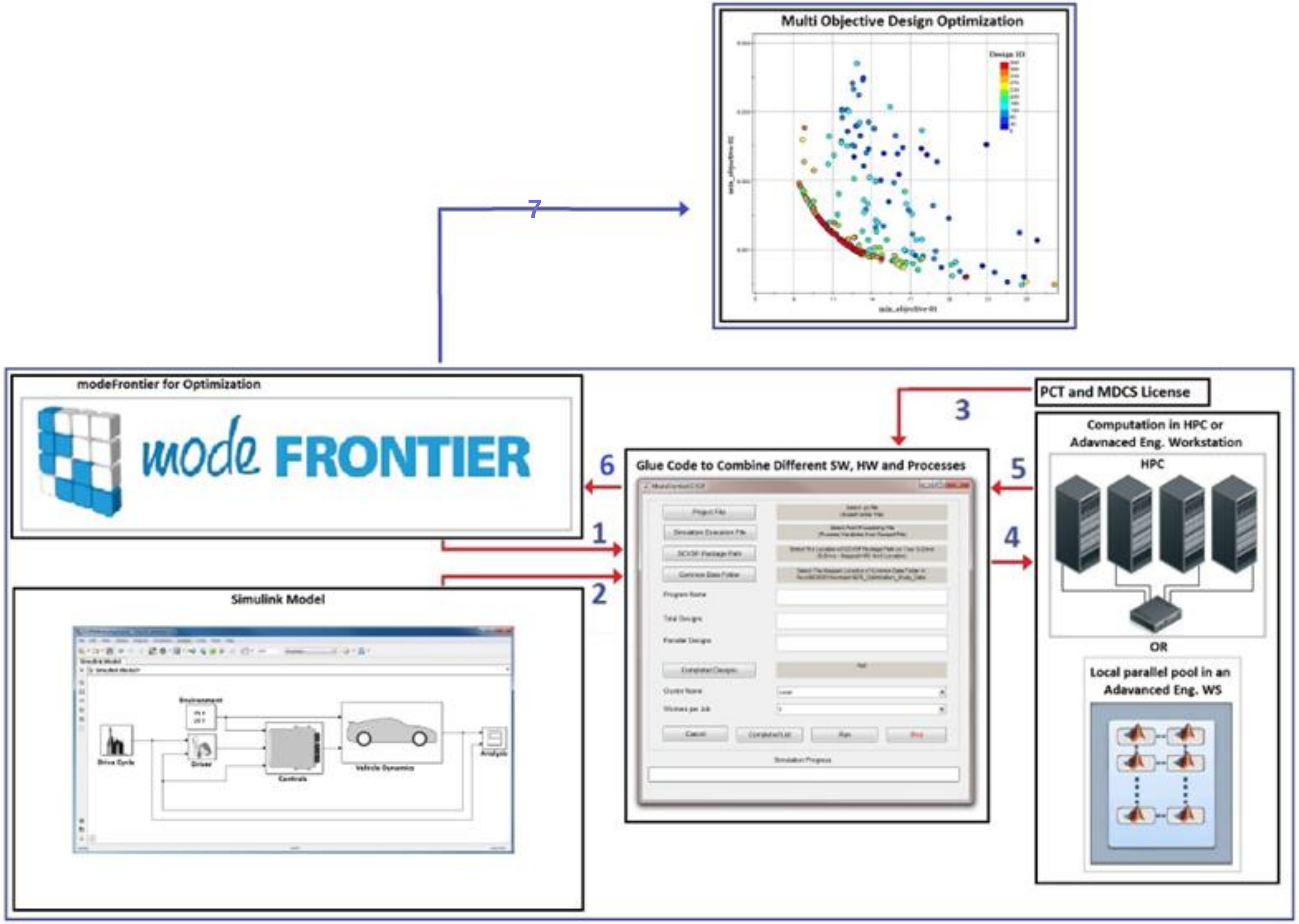
Simulations



- **Frame cal. development as a mathematical optimization problem**
- **Generate a large data set with simulations**
- **Analytics/insight into complex system behavior**

2. Optimization Workflow

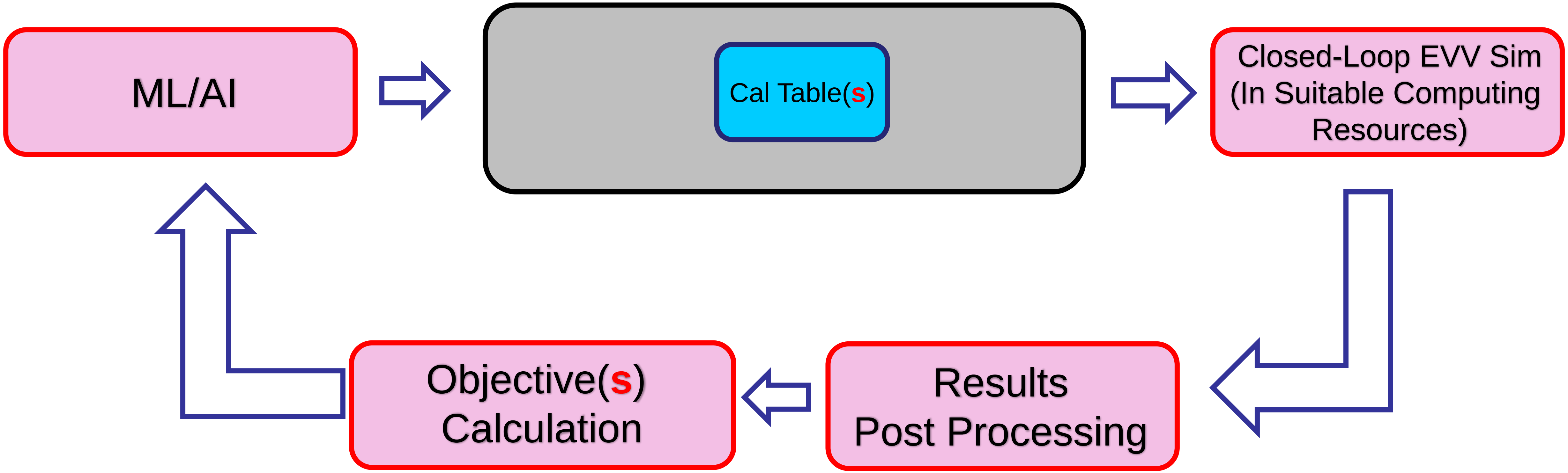
Model Based Cal. Optimization (MBCO) Ecosystem



In-house developed eco-system which utilizes Genetic Algorithms for optimization

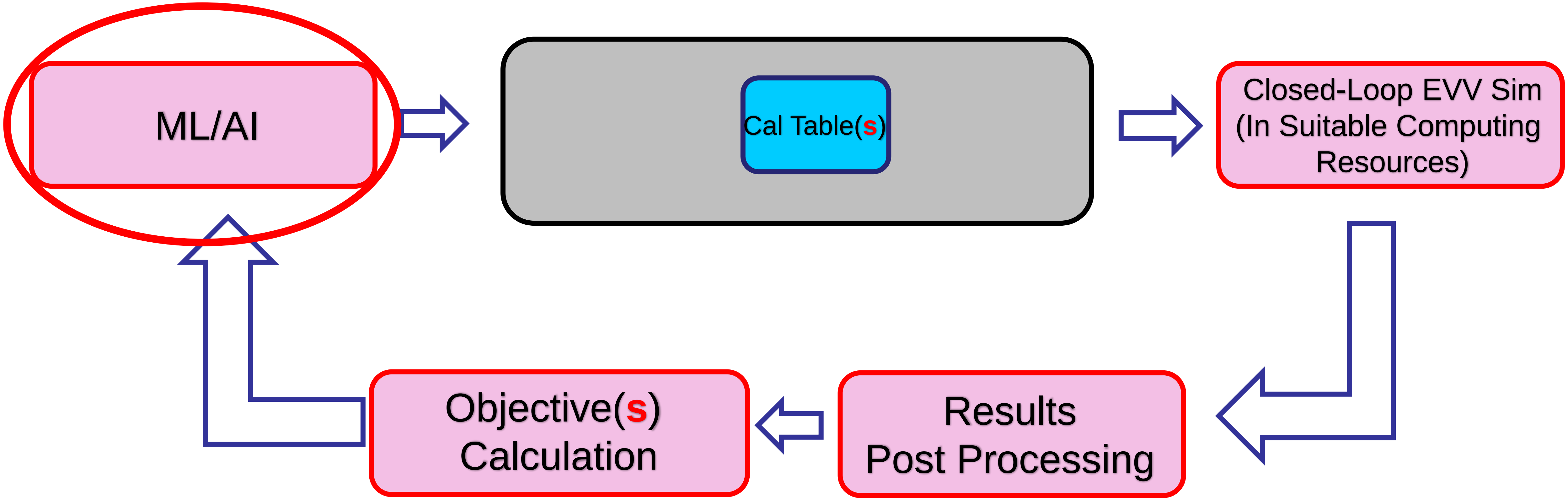
1. Design tables from modeFrontier software
2. Simulink based SiL Model
3. Cost-effective parallel computing license (PCT/MDCS)
4. Simulations run inside Ford HPC
5. Results Reported back to MBCO Ecosystem
6. Post processed results reported to the Genetic Algorithms
7. Data Analytics and Deployment

Calibration Optimization Workflow

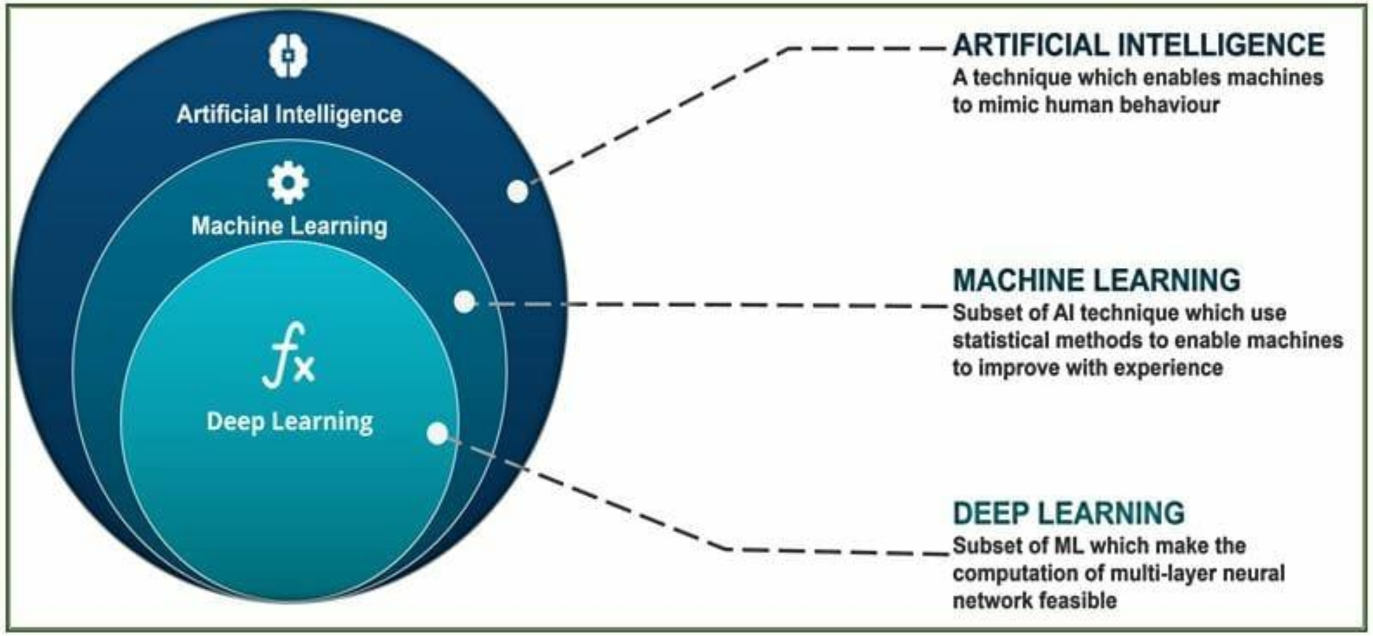


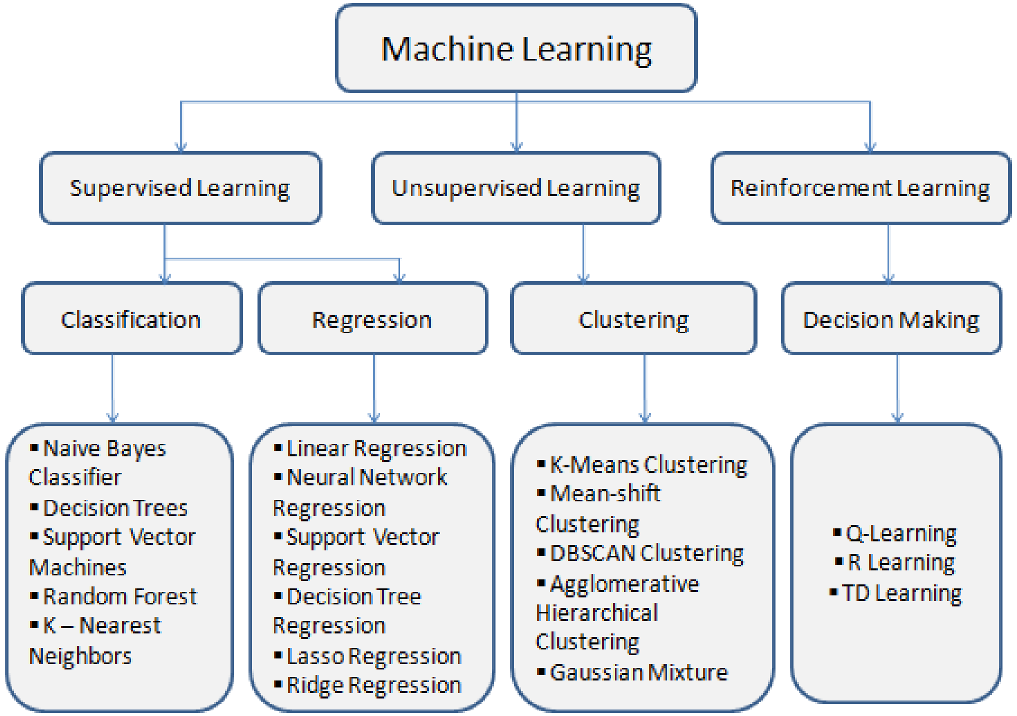
2.1 Selection of Machine Learning Algorithms

Calibration Optimization Workflow



AI vs ML vs DL

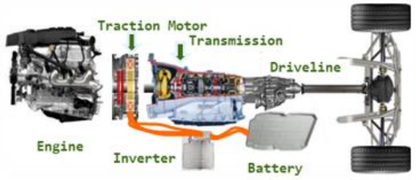

Artificial Intelligence
Machine Learning
Deep Learning
ARTIFICIAL INTELLIGENCE
A technique which enables machines to mimic human behaviour
MACHINE LEARNING
Subset of AI technique which use statistical methods to enable machines to improve with experience
DEEP LEARNING
Subset of ML which make the computation of multi-layer neural network feasible

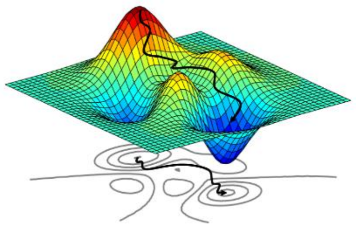

Machine Learning
Supervised Learning
Unsupervised Learning
Reinforcement Learning
Classification
Regression
Clustering
Decision Making
▪ Naive Bayes Classifier
▪ Decision Trees
▪ Support Vector Machines
▪ Random Forest
▪ K – Nearest Neighbors
▪ Linear Regression
▪ Neural Network Regression
▪ Support Vector Regression
▪ Decision Tree Regression
▪ Lasso Regression
▪ Ridge Regression
▪ K-Means Clustering
▪ Mean-shift Clustering
▪ DBSCAN Clustering
▪ Agglomerative Hierarchical Clustering
▪ Gaussian Mixture
▪ Q-Learning
▪ R Learning
▪ TD Learning

Selection of Machine Learning Algorithms

- Electrified vehicles are complex electro-mechanical systems
  - Sophisticated control systems in multiple control modules
  - Control system could be calibrated to achieve different attributes
- Makes calibration process complex and time intensive
  - Large number of individual calibration constants in one controller only
  - Interconnected 3D tables
- Infinite number of calibration combinations
- Need to run large number of simulations to find mathematical global optimum
- High fidelity models – higher computation time

- ML Algorithm should be able to handle this scale
  - Run evaluations as batches (for parallelization)
- Genetic Algorithms (subset of Evolutionary Algorithms) was selected





Part of a series on the
Evolutionary algorithm
Artificial development · Artificial life · Cellular evolutionary algorithm · Cultural algorithm · Differential evolution · Effective fitness · Evolutionary computation · Evolution strategy · Gaussian adaptation · Evolutionary multimodal optimization · Particle swarm optimization · Memetic algorithm · Natural evolution strategy · Neuroevolution · Promoter based genetic algorithm · Spiral optimization algorithm · Self-modifying code · Polymorphic code

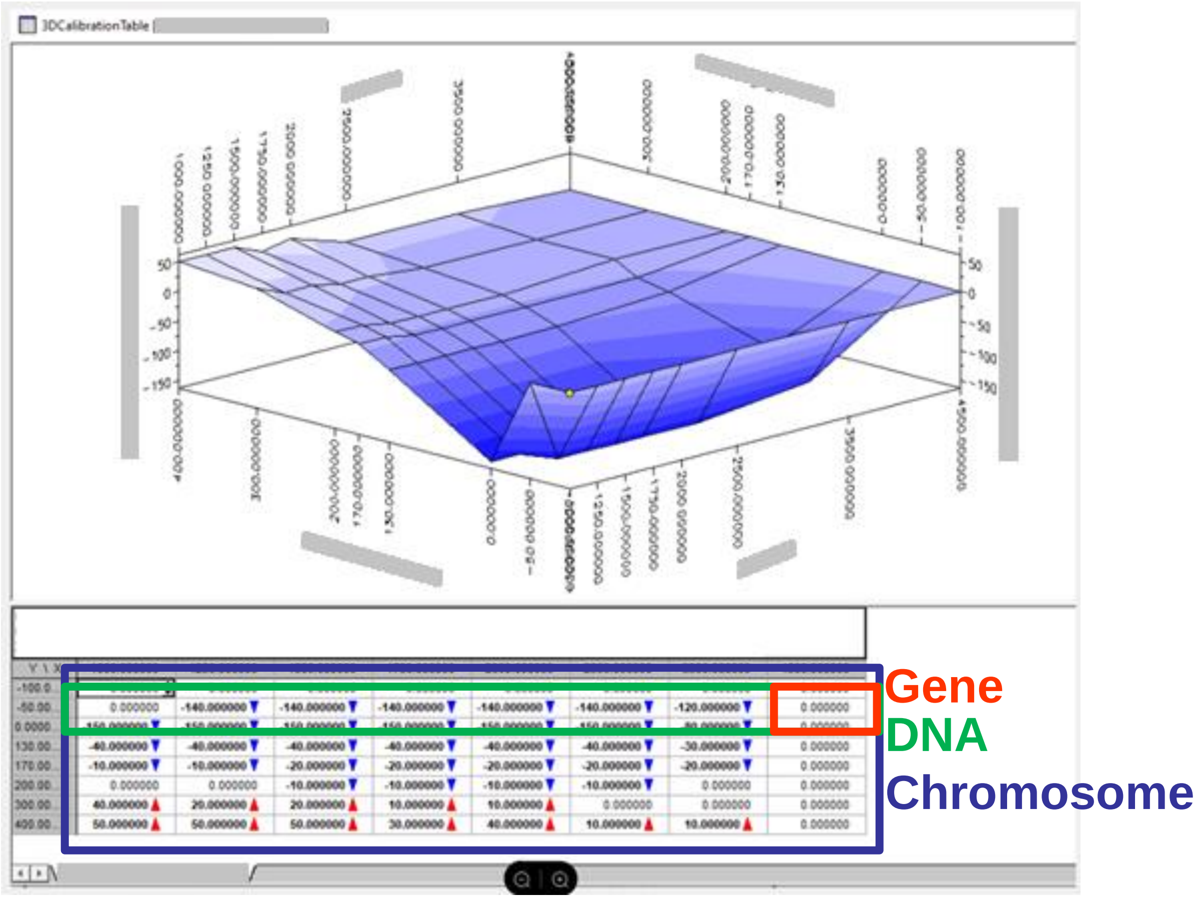
Genetic algorithm
Chromosome · Clonal selection algorithm · Crossover · Mutation · Genetic memory · Genetic fuzzy systems · Selection · Fly algorithm

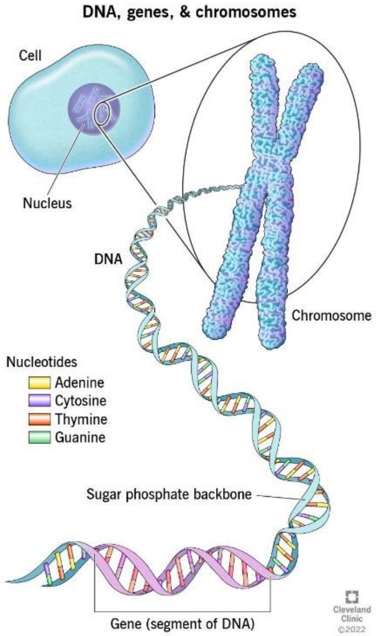
Genetic programming
Cartesian genetic programming · Linear genetic programming · Grammatical evolution · Multi expression programming · Genetic Improvement · Schema · Eurisko · Parity benchmark

V · T · E

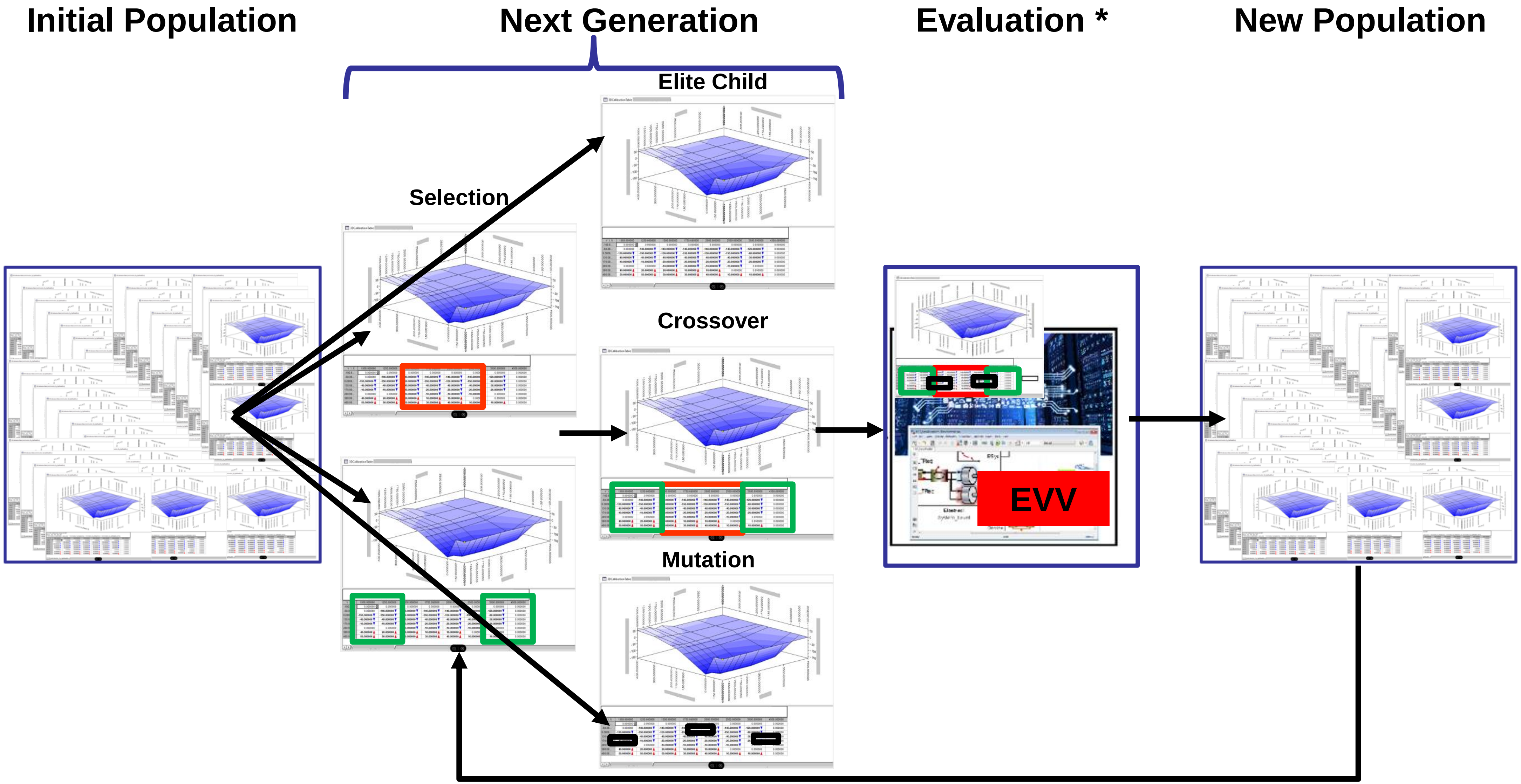
Application of GA to Calibration Optimization

- Let us consider one example calibration table
- Different calibration values in this table yields different fuel economies for the vehicle
- We treat single combination of this table as an individual in a population



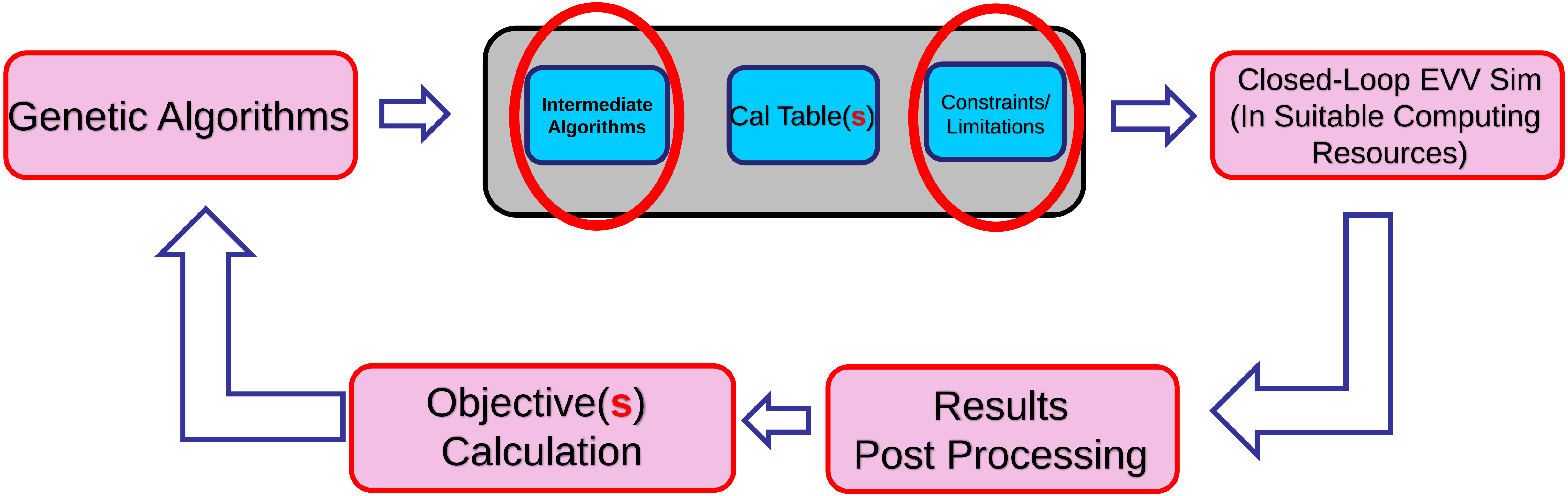


Application of GA to Ford Calibration Optimization



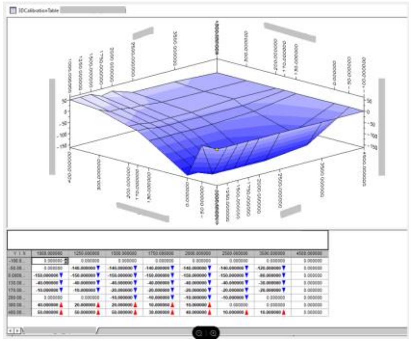
2.2 Development of Customized/Intermediate Algorithms

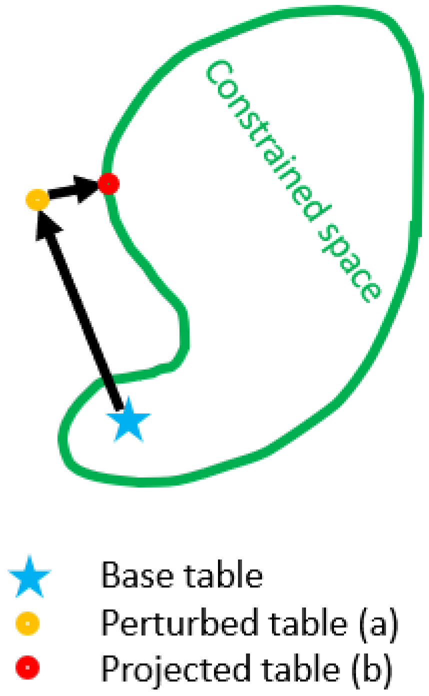
Calibration Optimization Workflow



Study Specific Intermediate Algorithms and Constraints

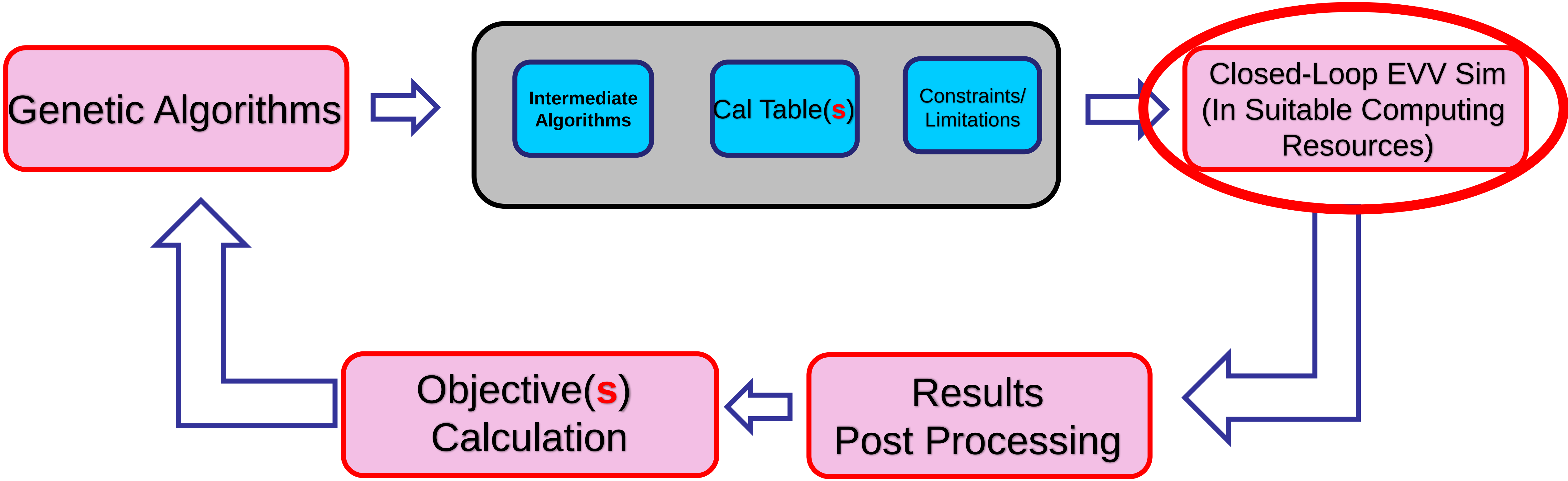
- Presented before was an 8x8 (64 element) table
- 10 of similar tables are included in one study
  - ~640 elements
  - 640 DOF
- Application specific, special “Intermediate Algorithms" are needed to
  - Reduce this dimensionality
  - Couple calibration tables to GA
  - Maintain shape factors / constraints
- GA algorithm suggests a “statistical – black box” table
- Constraints may have to be applied to make them feasible in reality
  - GAs handle the problem as a black box optimization
  - Without physics or constraints
  - Constraints application make them production ready





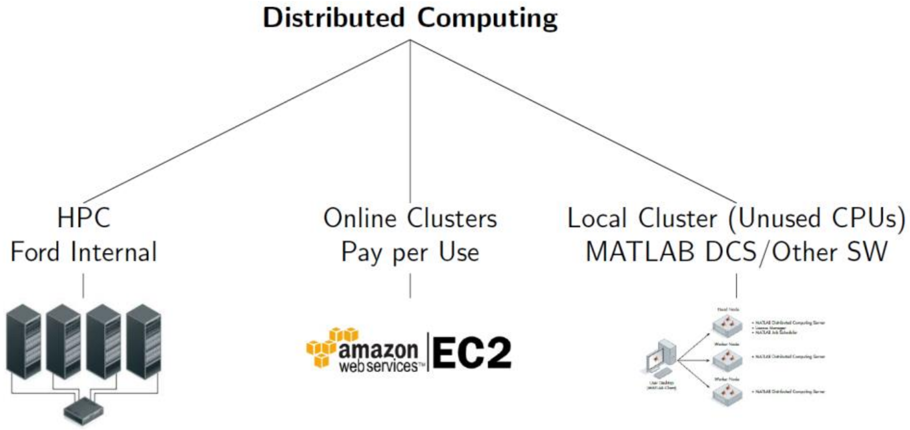
2.3 Finding Computing Resources to Run Parallel Simulations

Calibration Optimization Workflow



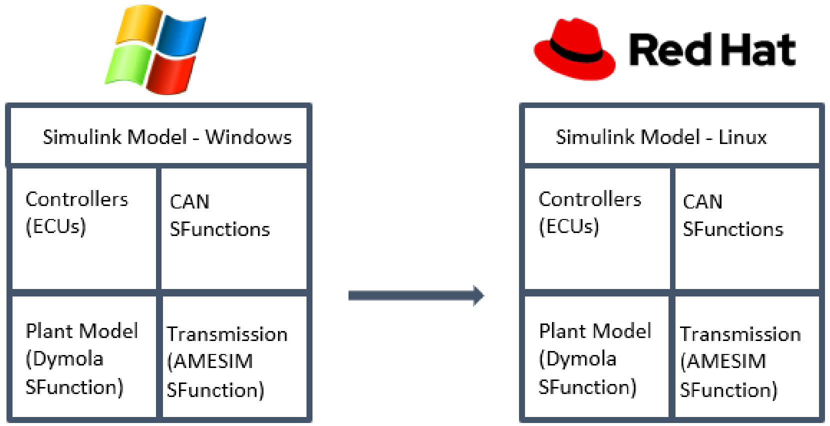
Computing Resources

- Need a cost-effective computing resource to run optimization studies



- Ford Central HPC is selected
  - Data security
  - Cost effectiveness

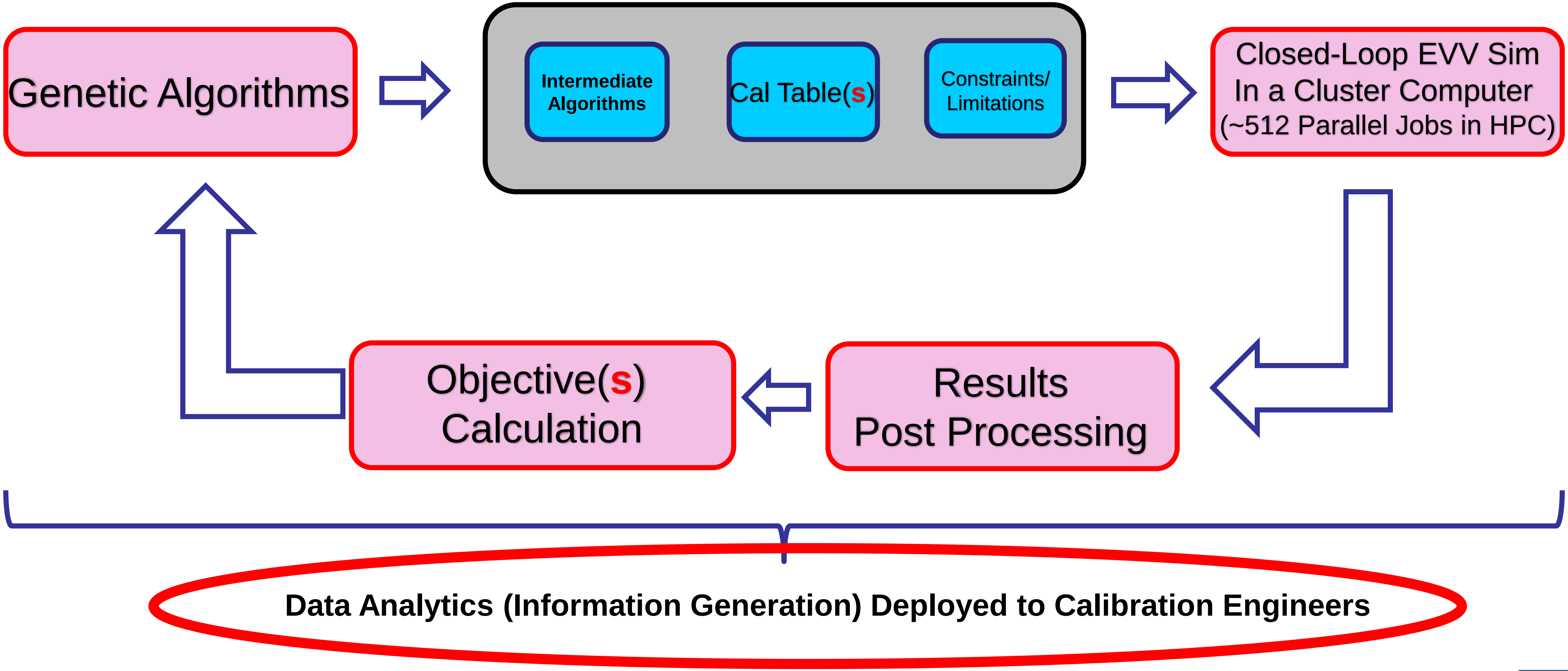
- Challenges with scaling up (512 parallel jobs in Linux HPC)
  - Windows to Linux recompilation needed
    - Ford Central HPC runs on Linux OS
  - License requirements for co-sim/model exchange components
  - Compilation compatibility of certain source codes



MBCO

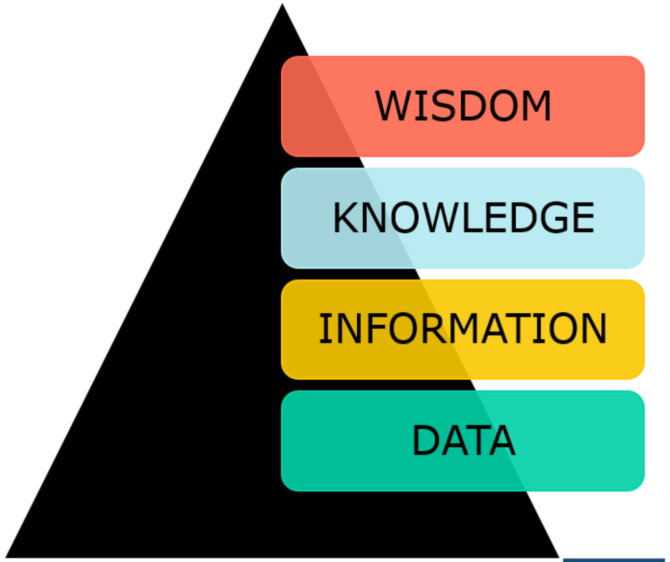
2.4 Data Analytics and Deployment to Internal Partners (Calibration Engineers)

Calibration Optimization Workflow



Data Analytics

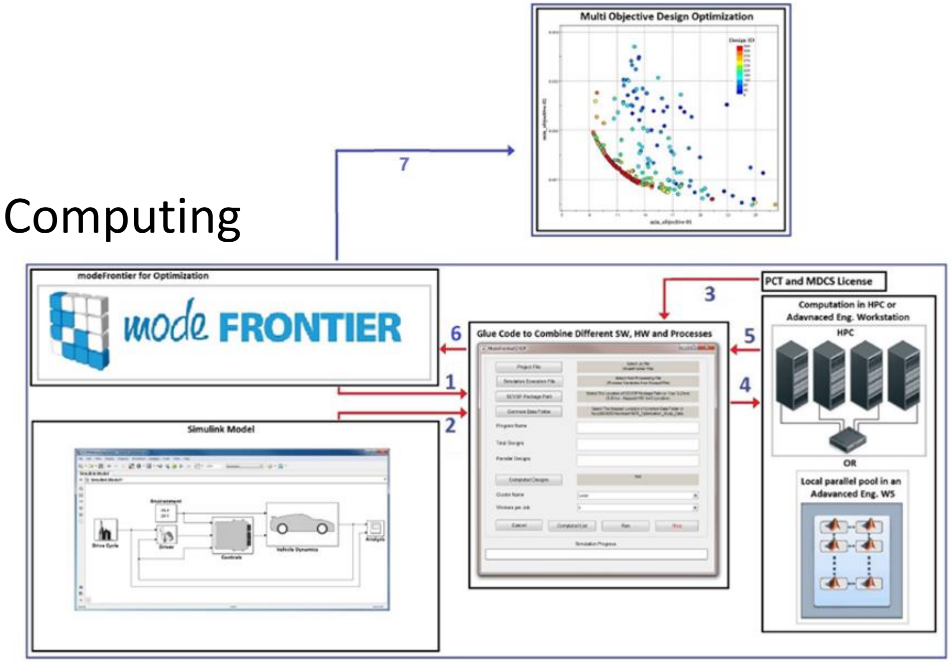
- Mechanism to deliver the information/knowledge to calibration engineers
  - Statistical Analysis
  - Physics based time domain analysis
- Typical MBCO study will generate ~250+ GB worth of data
  - ~10,000+ different calibrations
  - Best calibration (1) Vs everything (~10,000+) as a source of information
- Data —Analytics→ Information
- Collaboration with calibration engineers
  - Reusing existing tools
  - Developing new tools/processes
- In-house development with MATLAB + other tools



2.5 System Level Integration of all Components with MBCO Ecosystem

Current MBCO Ecosystem Capabilities

- **Running Multi Objective (Attributes) – Multi Constraint Optimization**
  - Using DOEs or Genetic Algorithms
- **Scalable for Parallel Computing of Simulink Jobs**
  - 1 CPU (Sequential) in a PC to up to 512 CPUs in Parallel Cluster Computing
- **Time Capability Comparison**
  - 8000 CAE Simulations (3.5 Hours per each simulation)
  - Sequential computing needs 28000+ hours
  - Completed in 96 hours with 400 parallel processes
  - Physical testing would need ~30+ years



$$\frac{28000}{96} = 291.7\ ?$$

Parallelization Overhead + Data Transfer

3. Sample Study Results

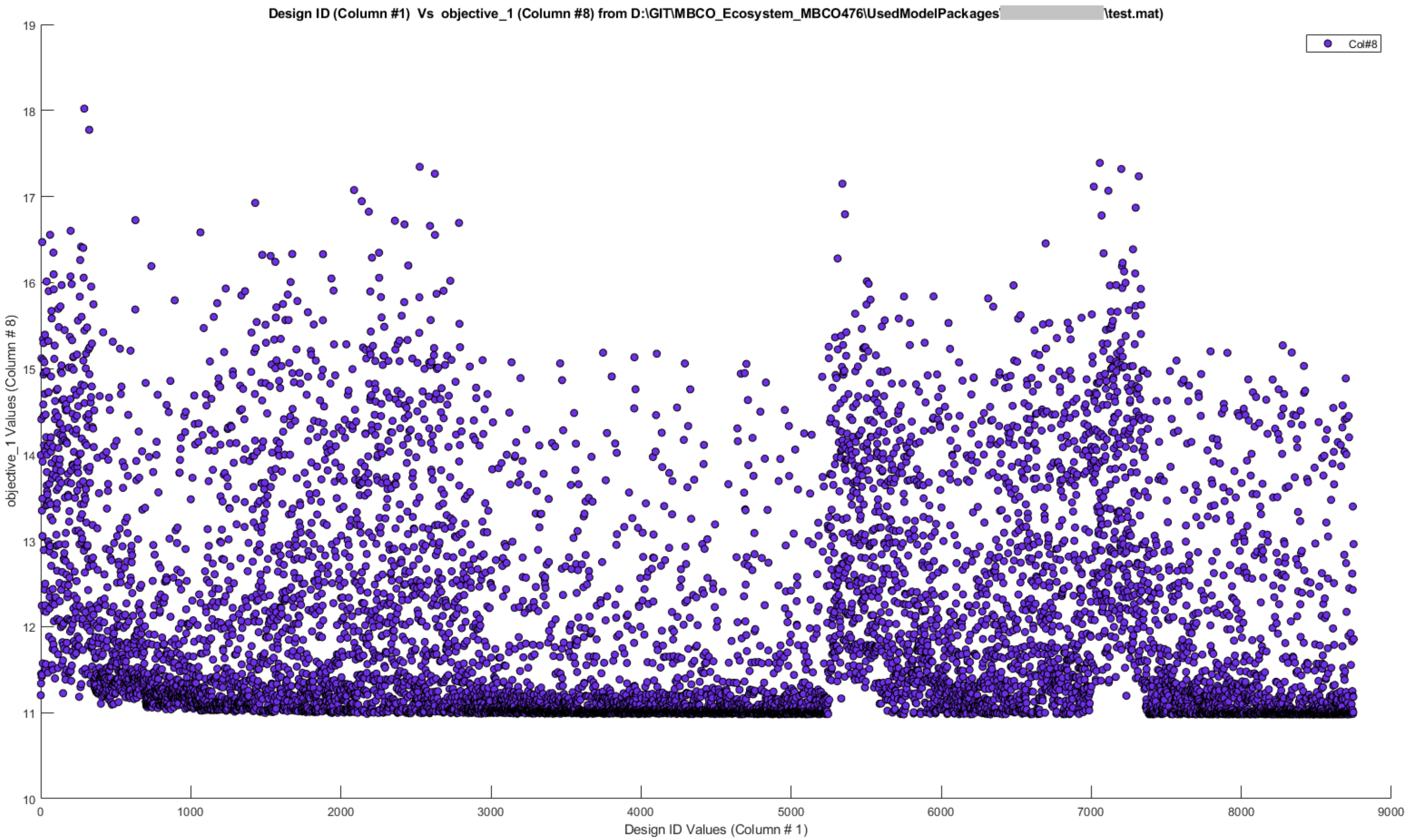
Details

- This study was carried out to maximize the fuel economy of one of our xEV program
- 4 tables were included as calibration constants
  - 4 – 12x17, 25x9, 25x17, 12x17 2D tables
- 553 elements (~553 DOF)
- Coupled to GA via an “intermediate algorithm”
  - To reduce dimensionality
  - Maintain shaper factors / impose constraints
  - DOF was reduced to 121 from 553
- 8750 different calibrations were suggested by GAs and evaluated
  - Population size – 350
  - Populations - 25

Results

8752x12 cell

	1	2	3	4	5	6	7	8	9	10	11	12
1	'Design ID'	'table_1'	'table_2'	'table_3'	'table_4'	'table_5'	'table_6'	'objective_1'	'output_2'	'output_3'	'output_4'	'output_5'
2	'Base'	1x1 struct	1x1 struct	1x1 struct	1x1 struct	1x1 struct	1x1 struct	0	0	0	0	0
3	0	12x17 uint16	25x9 uint16	25x17 uint16	12x17 uint16	25x9 uint16	25x17 uint16	11.2027	0.7855	65	65	53.4465
4	1	12x17 uint16	25x9 uint16	25x17 uint16	12x17 uint16	25x9 uint16	25x17 uint16	13.9941	0.7856	65	65	50.6642
5	2	12x17 uint16	25x9 uint16	25x17 uint16	12x17 uint16	25x9 uint16	25x17 uint16	11.3401	0.7855	65	65	53.3036
6	3	12x17 uint16	25x9 uint16	25x17 uint16	12x17 uint16	25x9 uint16	25x17 uint16	1				
7	4	12x17 uint16	25x9 uint16	25x17 uint16	12x17 uint16	25x9 uint16	25x17 uint16	1				
8	5	12x17 uint16	25x9 uint16	25x17 uint16	12x17 uint16	25x9 uint16	25x17 uint16	1				
9	6	12x17 uint16	25x9 uint16	25x17 uint16	12x17 uint16	25x9 uint16	25x17 uint16	1				
10	7	12x17 uint16	25x9 uint16	25x17 uint16	12x17 uint16	25x9 uint16	25x17 uint16	1				
11	8	12x17 uint16	25x9 uint16	25x17 uint16	12x17 uint16	25x9 uint16	25x17 uint16	1				
12	9	12x17 uint16	25x9 uint16	25x17 uint16	12x17 uint16	25x9 uint16	25x17 uint16	1				
13	10	12x17 uint16	25x9 uint16	25x17 uint16	12x17 uint16	25x9 uint16	25x17 uint16	1				
14	11	12x17 uint16	25x9 uint16	25x17 uint16	12x17 uint16	25x9 uint16	25x17 uint16	1				
15	12	12x17 uint16	25x9 uint16	25x17 uint16	12x17 uint16	25x9 uint16	25x17 uint16	1				
16	13	12x17 uint16	25x9 uint16	25x17 uint16	12x17 uint16	25x9 uint16	25x17 uint16	1				
17	14	12x17 uint16	25x9 uint16	25x17 uint16	12x17 uint16	25x9 uint16	25x17 uint16	1				
18	15	12x17 uint16	25x9 uint16	25x17 uint16	12x17 uint16	25x9 uint16	25x17 uint16	1				
19	16	12x17 uint16	25x9 uint16	25x17 uint16	12x17 uint16	25x9 uint16	25x17 uint16	1				
20	17	12x17 uint16	25x9 uint16	25x17 uint16	12x17 uint16	25x9 uint16	25x17 uint16	1				
21	18	12x17 uint16	25x9 uint16	25x17 uint16	12x17 uint16	25x9 uint16	25x17 uint16	1				

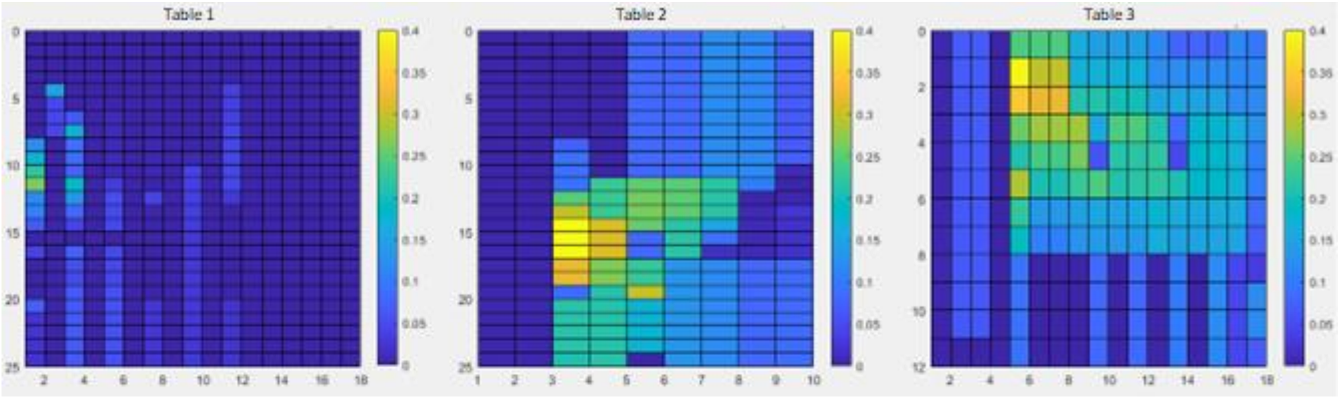


Data Analysis and Deployment

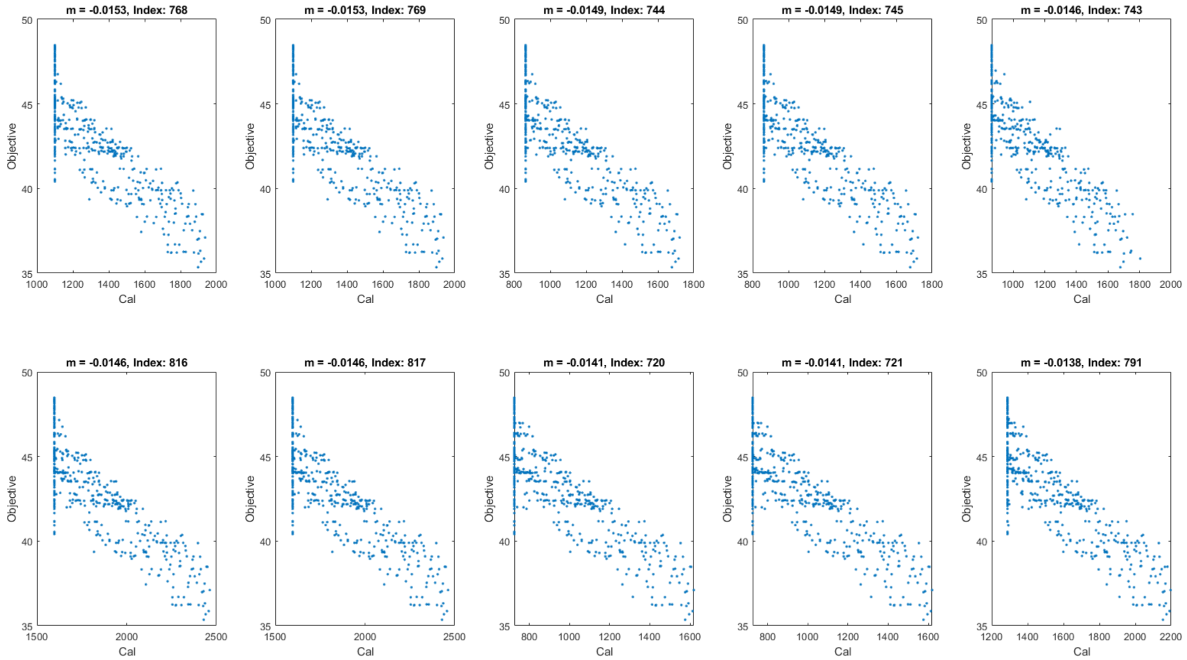
- Objective is to provide insight for calibration engineers
- Questions to answer:
  - What regions of the calibration tables provide opportunity for improvement?
  - What are the requirements for optimality?
  - How robust are the calibrations?
  - Is the path to optimality unique or can it be achieved in multiple ways?
- These questions are answered using statistical/ML methods
- Methods:
  - Statistical significance tests to identify the regions of the tables modified by the optimization process
  - Provide requirements for optimality and robustness in terms of a confidence interval using the top x% results
  - Sensitivity analysis to identify important regions of the calibration tables
  - Clustering methods to identify different paths for improvements
- Many of these same methods are used to identify how the optimal calibrations achieve the optimality by analyzing how the calibrations are linked to objective via intermediate performance indicators

Data Analysis and Deployment

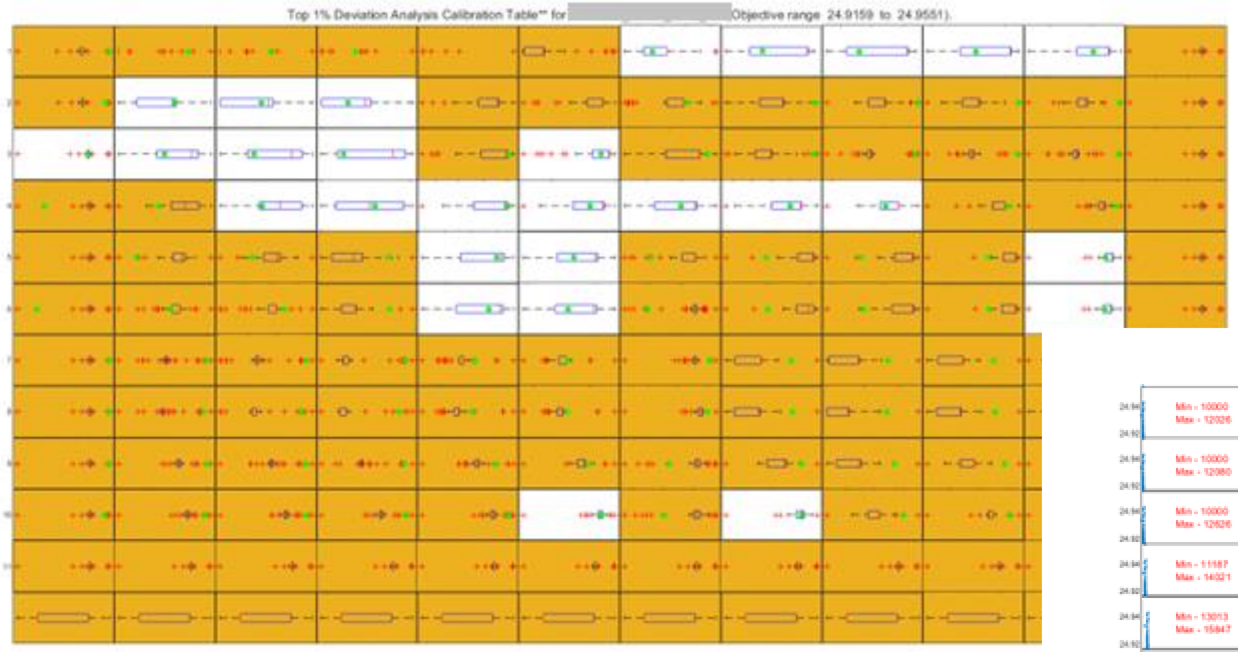
- Heatmap showing the significant areas of the calibration tables modified by the optimization algorithm



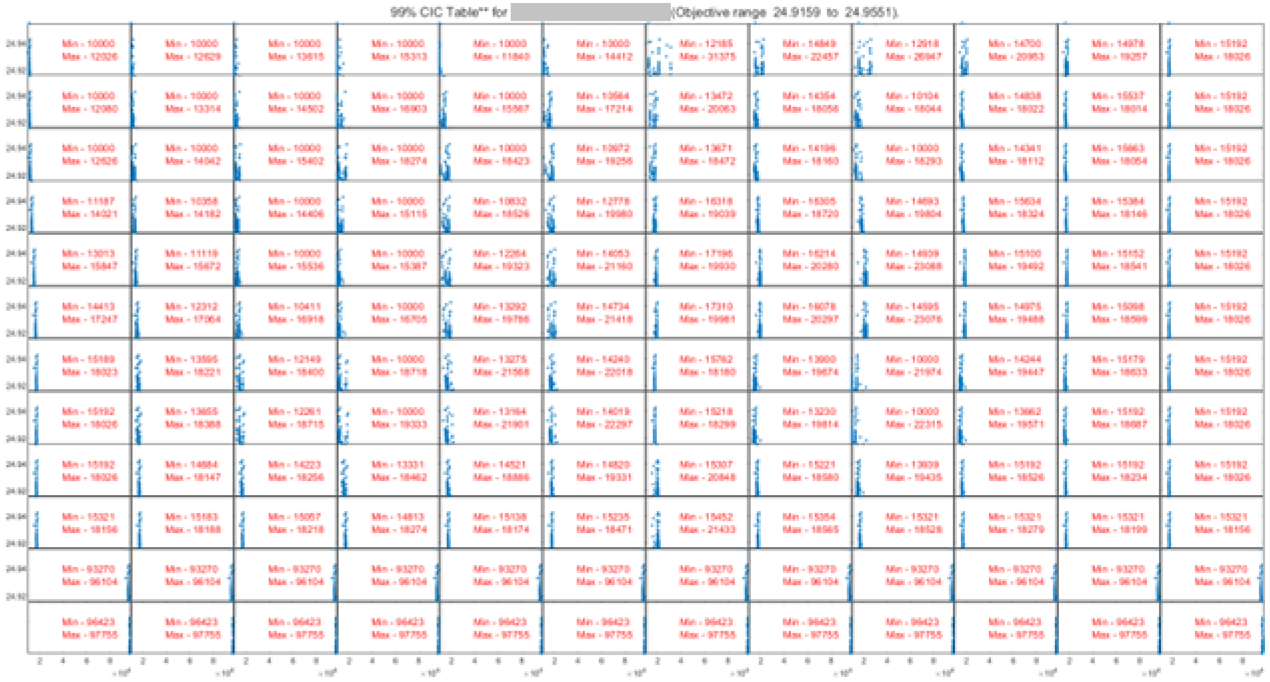
- Calibrations that have the most effect on the objective



Data Analysis and Deployment



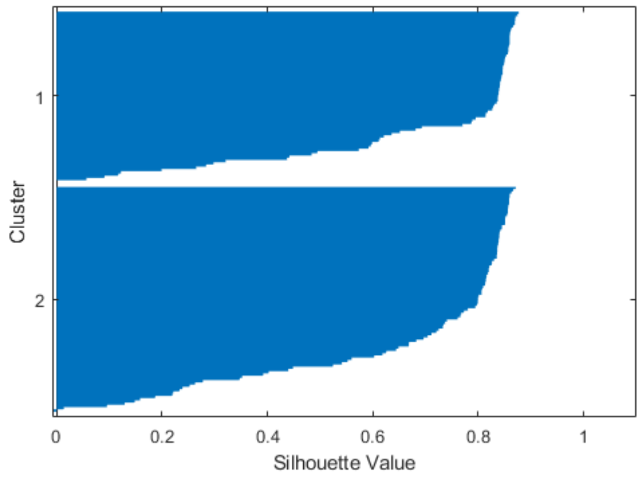
- Distribution of top X% calibrations compared to the base calibration

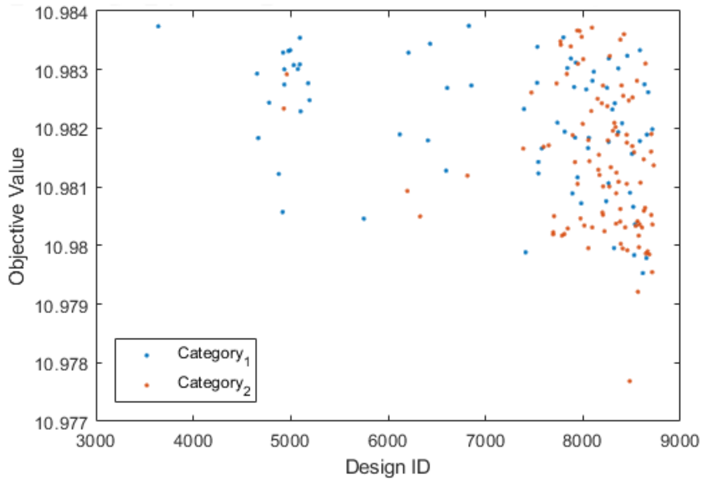


- Necessary conditions for optimality with X% confidence intervals

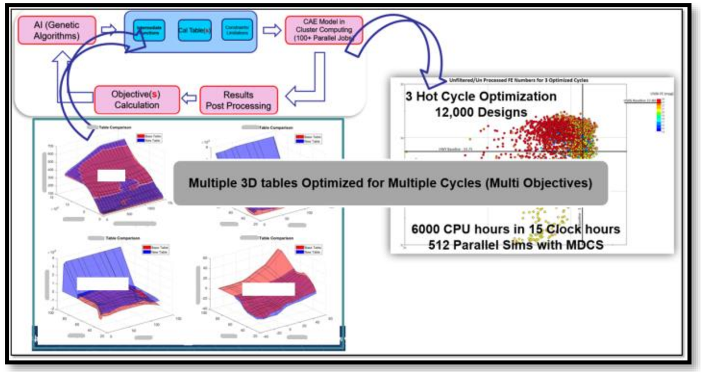
Data Analysis and Deployment

- Clustering to identify whether there are multiple classes of calibration tables that achieve values in the top X%

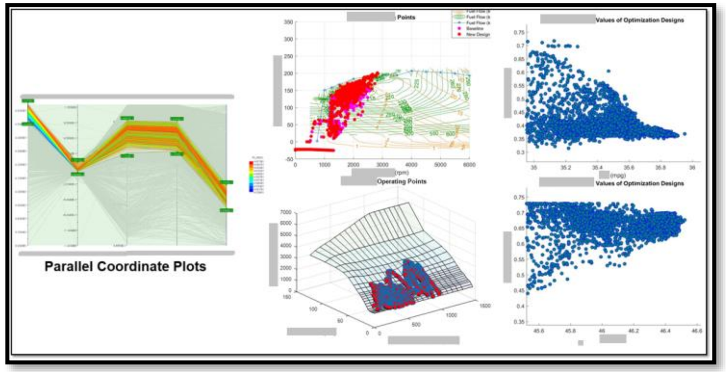




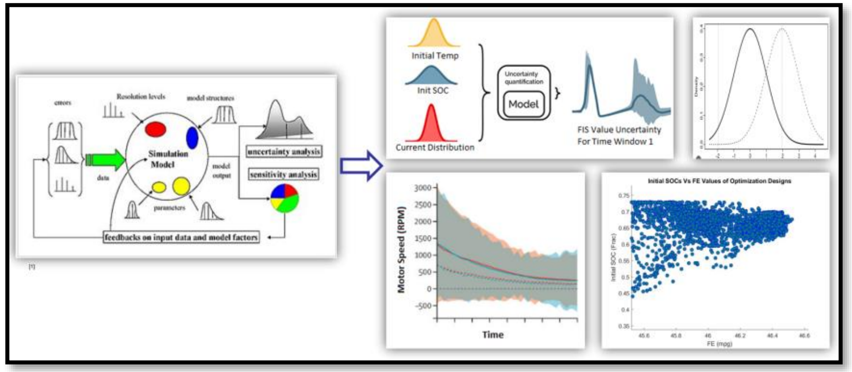
Data Analysis and Deployment (In-Progress)



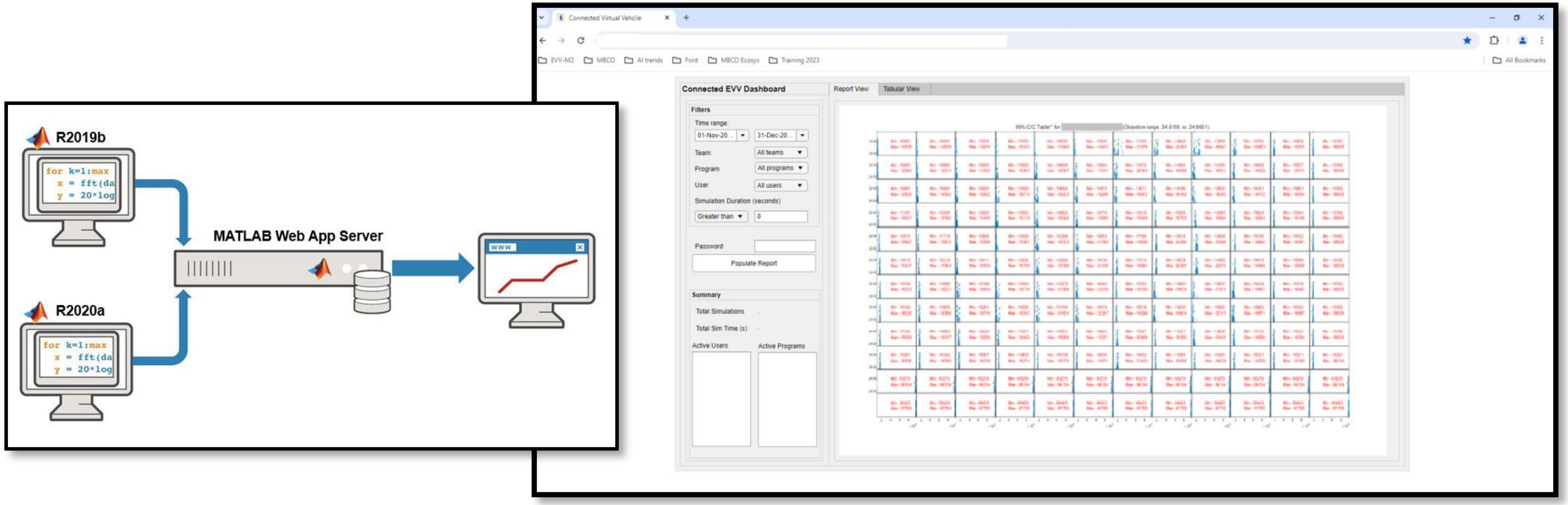
Multi Objective Optimization



System Behavior Analytics



Sensitivity/Robustness Analytics



Deployed as a MATLAB Web App to Calibration Engineers

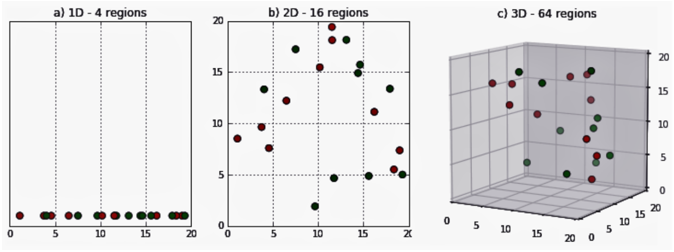
4. Challenges

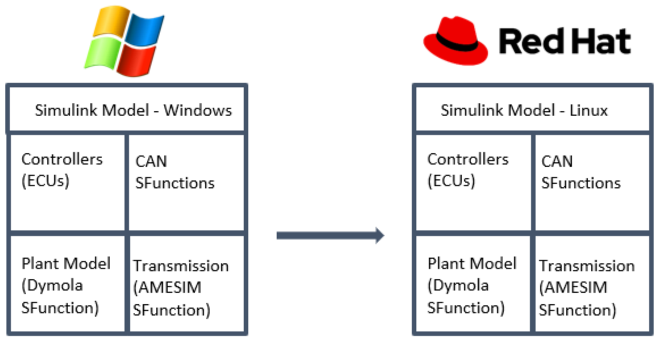
Challenges

- Methodology
  - Curse of dimensionality
  - Effects of test vehicles and driver behavior variability
  - Model limitations
  - “Human practices Vs Mathematical concepts” gap

- Technical
  - Converting Windows models to Linux (for HPC)
  - Handling large amounts of data generated

- General
  - Going from limited production to full production





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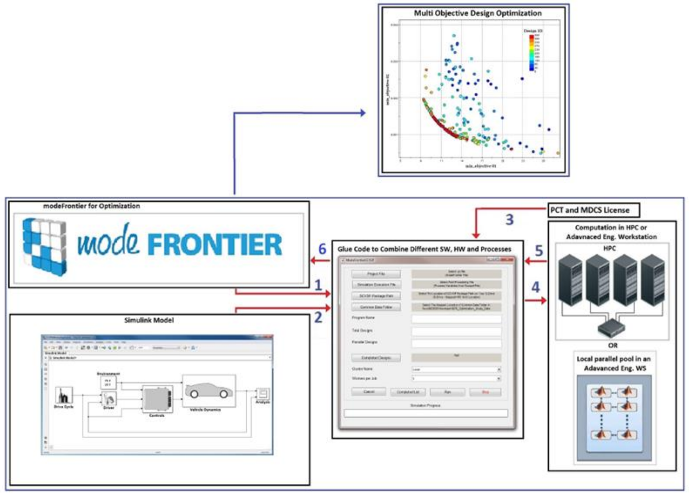
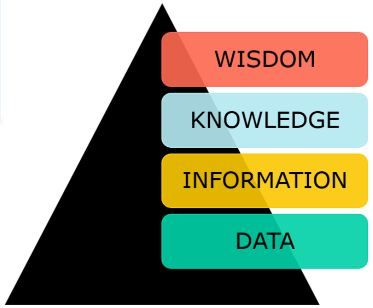
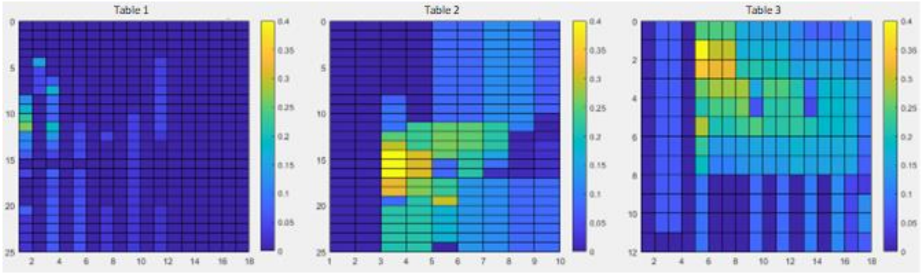
Key Takeaways

- Objective is to assist calibration engineers with model-based optimization studies in a scale that's not possible with test vehicles
- MBCO Ecosystem was built to facilitate this goal by making use of the MDCS, Ford internal HPC clusters and modeFrontier
- Powertrain calibration is posed as a mathematical optimization problem and addressed via a Genetic algorithm combined with intermediate algorithms
- Analysis wizards were created to generate insights based on optimization results to assist calibration tasks
- Current pilot studies are being successfully carried out with the intention of full deployment soon







Acknowledgements

- Ben Nault
  - Manager, Cyber Calibration Team @ Ford
- Shuzhen Liu
  - Supervisor, MBCO Team @ Ford
- Model Based Calibration Optimization Team
  - Our home team @ Ford
- Powertrain Calibration Teams
  - Our internal partners (customers) @ Ford
- MathWorks Team