Machine Learning for 100kW SiC In-Wheel Inverter Package Design: Project Introduction

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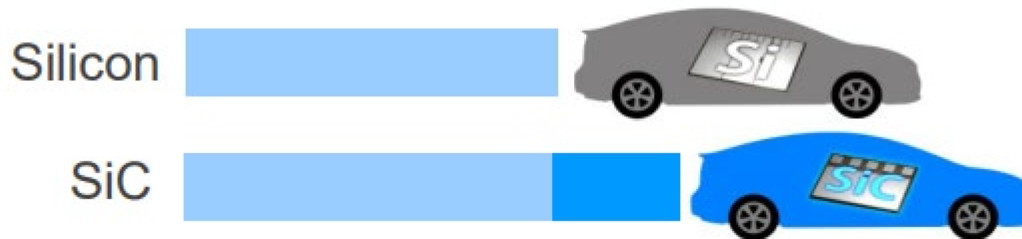
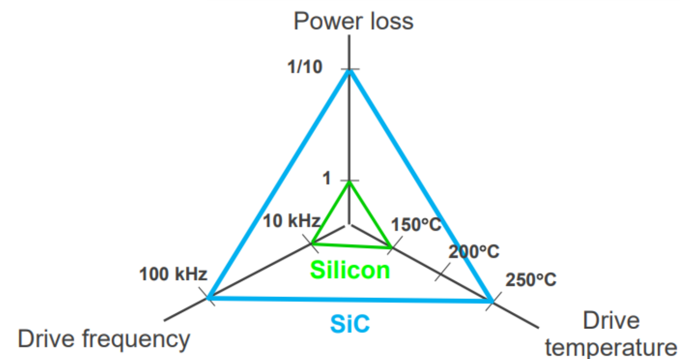
Outline

- Goals & Objectives
- Prior Art
- Technical Approach
- Results & Key Accomplishments
- Comparison with Prior Art
- Schedule
- Summary

Goals and Objectives



Metrics	Objectives
Size Reduction	> 25%
Power Density	100 kW per Wheel
Temperature	> 150°C (T_{jmax}=250°C)
Carrier Frequency	> 10 kHz



B. K. Chakravarthy and G. Sree Lakshmi, "Power Savings with all SiC Inverter in Electric Traction applications," *E3S Web Conf.*, vol. 87, pp. 1-14, 2019.

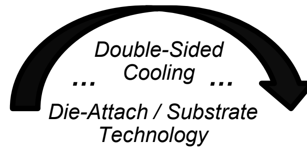
- Create an automated package design optimization tool combining **multi-physics modeling** and **machine learning** (ML) to expedite the design of next-generation SiC-based in-wheel inverters with superior power density and efficiency for improved fuel economy.

- Based on predictions from ML algorithm, **build and test** new package structures.

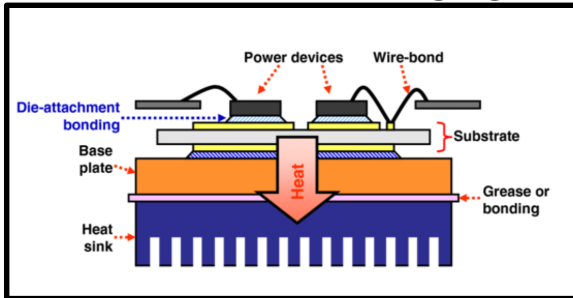
Architecture of Power Modules

Shaping the Landscape of SiC-Based Power Conversion

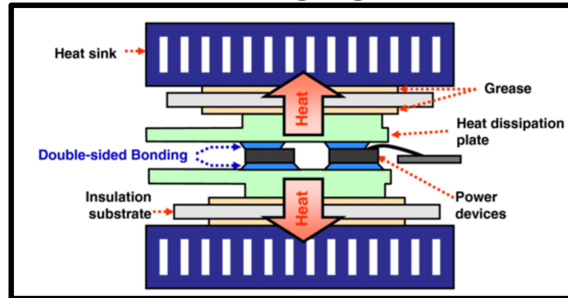
Incremental Innovations

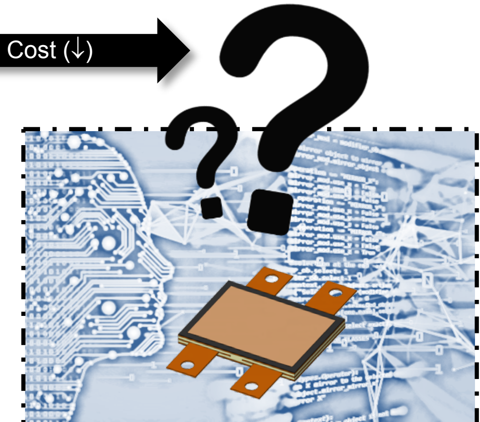


Conventional Packaging

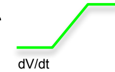


Advanced Packaging: Power Card





Si-Based Drive Inverters



SiC-Based Drive Inverters

SiC-Based Power Modules

ML-Enabled Disruptive Innovations

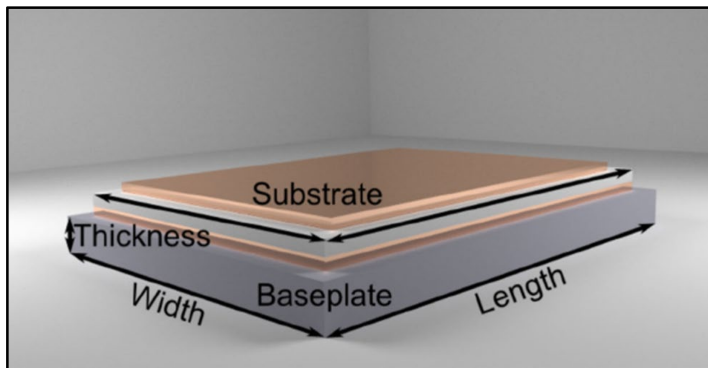
- Machine learning (ML) and active learning are key to developing disruptive packaging solutions to benefit fully from the performance advantages of SiC:
  - Efficient multi-objective optimization of package architectures (geometry, materials) with over 40 parameters
  - Long-term goal is for the model to self-generate new, non-intuitive architectures

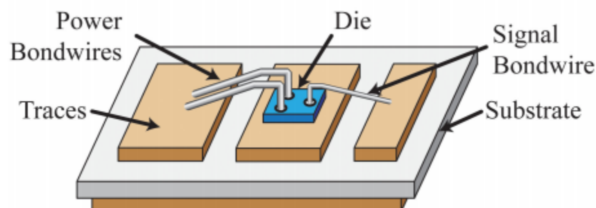
S. W. Yoon et al. "Reliable and repeatable bonding technology for high temperature automotive power modules for electrified vehicles," *J. of Micro Mech. and Microeng.*, 2012.

Examples of Use of Optimization Algorithms

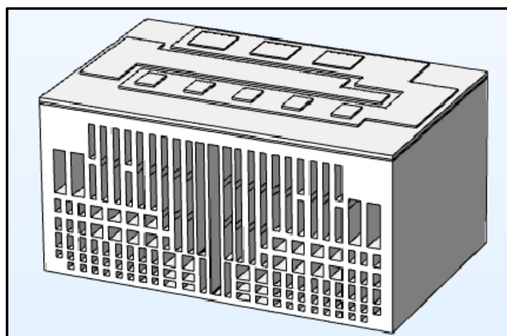
in Power Electronics Packaging

Power Module Stack-Up

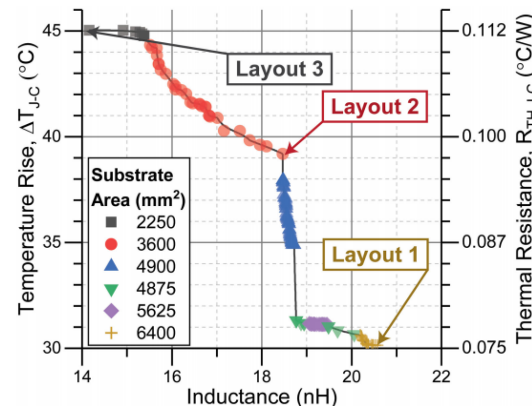


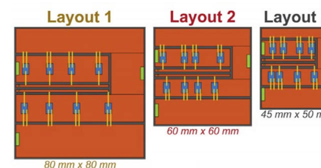


Heat Sink Geometry



Layout Optimization Pareto Frontier





	Optimization	Metric
Thermal	Die Area	Maximum Temperature Temperature Rise
	Die Position	
	Trace Area	
	Trace Position	
Electrical	Trace Width	Inductance
	Trace Length	

T. M. Evans *et al.*, "PowerSynth: A Power Module Layout Generation Tool," *IEEE Transactions on Power Electronics*, 2019.
T. Wu, B. Ozpineci, M. Chinthavali, W. Zhiqiang, S. Debnath, and S. Campbell, "Design and optimization of 3D printed air-cooled heat sinks based on genetic algorithms," in *IEEE ITEC*, 2017.

Comparison of Optimization Methods and their Scope

in (Power) Electronics Packaging

Optimization Methods

Category	Method
Regression Methods	Artificial Neural Networks
	Quadratic Response Surface
	Multiquadric Response Surface
	Response Surface
	Taylor Series Approximation
	Subapproximation Method
	Least-Squares Fit Method
	Design of Experiments
Optimization Algorithms	Genetic Algorithms
	Gradient Search Technique
	Conjugate Gradient Method
	Broyden-Fletcher-Goldfarb-Shanno Algorithm
	Pattern Search Method
	Simulated Annealing
	Subproblem Approximation and First-Order Methods
	Finite-Difference Gradient Method and Artificial Neural Network

Limitation of Parameters

Methodology	Input	Output
Genetic Algorithms	6	2
Simulated Annealing	3	2
Genetic Algorithm + Simulated Annealing	3	2
Genetic Algorithm + Artificial Neural Networks	4	3
Design of Experiments	3	1
Design of Experiments + Least-Squares Fit Method	4	2
Force-Directed Algorithm	3	3
Force-Directed Algorithm + Fuzzy Logic	4	2
Cluster Growth Algorithm	3	3
Partition-Drive Algorithm	3	2

H. Hadim and T. Suwa, "Multidisciplinary Design and Optimization Methodologies in Electronics Packaging: State-of-the-Art Review," *Journal of Electronic Packaging*, 2008.
Coulibaly, "METHODIC: a new CAD for electrothermal coupling simulation in power converters," in *IECON '98.*
J. Z. Chen, Y. Wu, C. Gence, D. Boroyevich, and J. H. Bohn, "Integrated electrical and thermal analysis of integrated power electronics modules using iSIGHT," in *APEC 2001*
G. Xiong, M. Lu, C. Chen, B. P. Wang, and D. Kehl, "Numerical optimization of a power electronics cooling assembly," in *APEC 2001*
S. Sridhar and H. J. Eggink, "Dealing with uncertainty in power loss estimates in thermal design of power electronic circuits," in *Conference Record of the 1999 IEEE Industry Applications Conference.*
D. Gopinath, Y. Joshi, and S. Azarm, "An integrated methodology for multiobjective optimal component placement and heat sink sizing," *IEEE Transactions on Components and Packaging Technologies*, 2005.
D. Gopinath, Y. K. Joshi, and S. Azarm, "Multi-objective placement optimization of power electronic devices on liquid cooled heat sinks," in *Annual IEEE Semiconductor Thermal Measurement and Management, 2001.*

Machine Learning based Power Module Optimization

Generate new power module

Bayesian Active Learning

Power Converter → Switching Type → Device Technology → Circuit Topology → Design Parameters

Search Space

Packaging Architecture → 3D → Interconnect Types → Cooling Solution → Material and Geometry Parameters

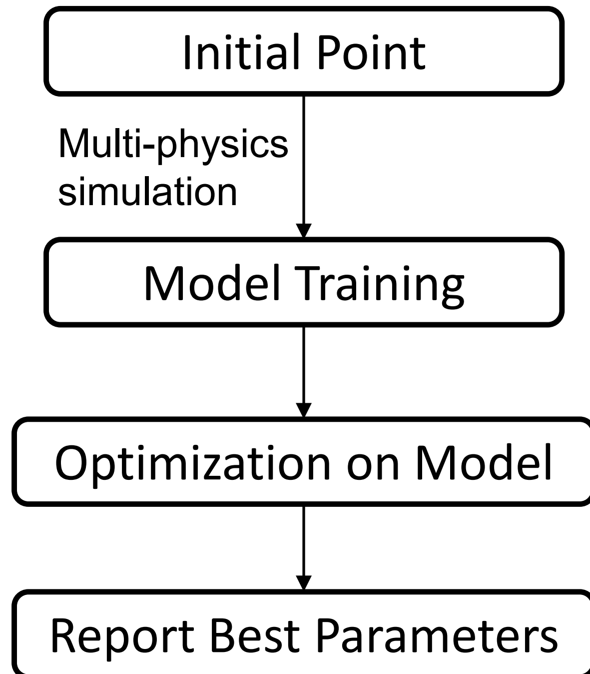
Multi-Physics Simulation

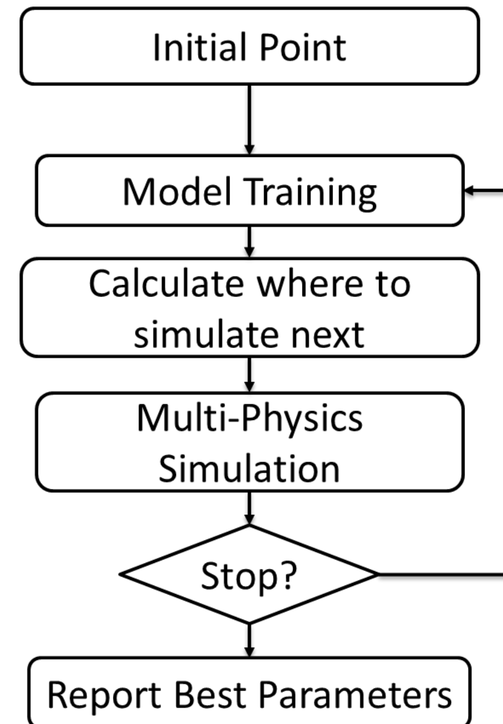
Electrical
Thermal
Mechanical

Performance Metrics:
dV/dt, power density, efficiency, thermal stability, volume, cost

- Power module optimization framework requires **Design, Technology and Package Co-Optimization.**
  - The best converter topology and package architecture combination, along with best design and material parameters.
- System is broken down to smallest possible building block at both circuit & package level.
- **Key:** Use Bayesian Active Learning (BAL) to determine the optimal combination of building blocks.
  - Along with quantifying the effect of choices on various performance metrics.

Comparison of Bayesian ML with existing approach





- Conventional approach to ML is to first collect data, then train the model.
  - Design of experiments methods (such as Latin Hypercube Sampling) are used to create the data.
- Active Learning (AL) is a sequential method that selects "what parameters" to be simulated
- AL techniques automatically create training data (starting from 0 data).
  - **Allows for building better quality models with less simulations!**
- Can be used for optimization and model building.

Overall Steps for ML

Circuit

Data Type: Continuous and categorical variables
Hard switching, soft switching, passives, device technology
Currently fixed as hard switching with IGBT devices (**STEP IV**)

Package Architecture

Data Type: Categorical variables
Wirebond, power card, 3D stacked, … + functional integration

Geometry & Material

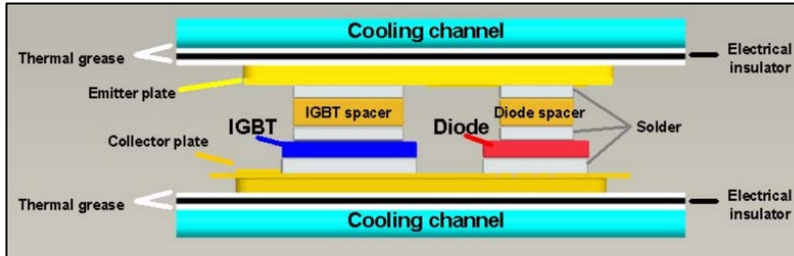
Data Type: Continuous and discrete variables
Current focus (STEP I): simplified problem to establish method capability → DENSO package, single physics (thermal), 10 continuous variables (geometry: layer thicknesses)

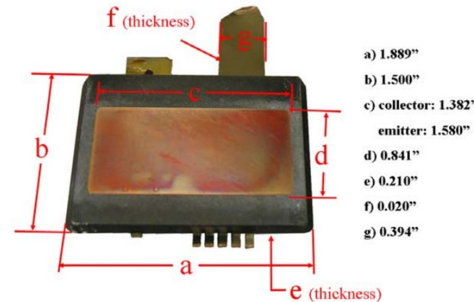
Cooling

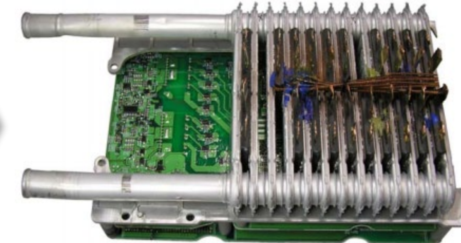
Data Type: Categorical and continuous
Heat pipe, heat sink, cold plate, integrated cooling, …
(Step III – explored in parallel through other Consortium project)

To Illustrate the Method: DENSO Power Card

Geometry for Multiphysics Modeling



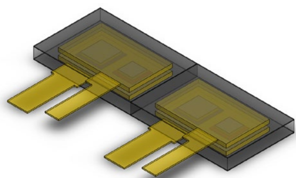




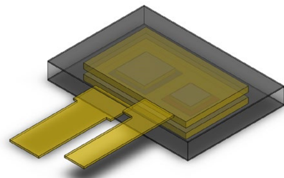
Lexus LS 600h Power Module (DENSO)

Multi-physics environment built in Ansys – for thermal solve:

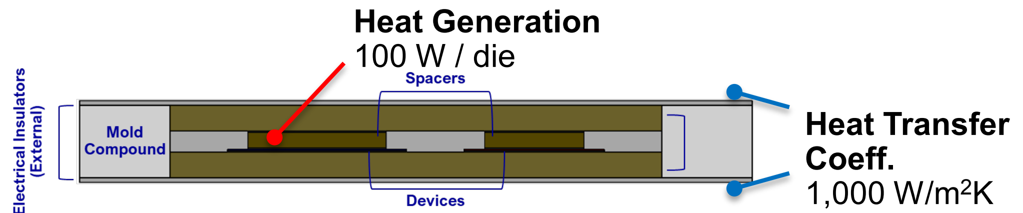
- Fully parameterized 3D model with simplified geometry
- Steady-state analysis as worst case thermal scenario
- Heat generated at switch and diode
- Double-sided liquid cooling represented as heat transfer coefficient
- Variations in thickness for initial thermal solve



Half-Bridge Configuration

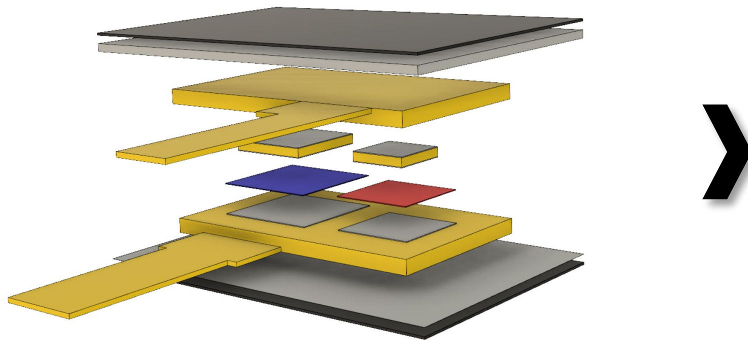


Compact Geometry



Initial Problem Definition: Thermal performance for DENSO Package

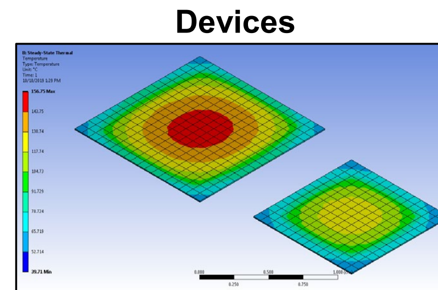
- 10 parameters define the geometry of the module (Z-direction)



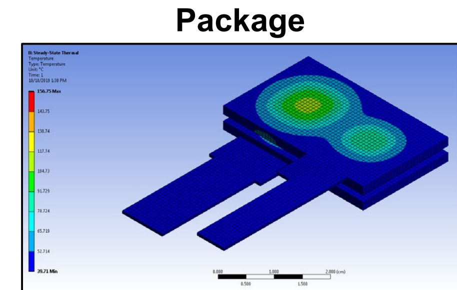
Parameter	Material	Unit	Min	Max
Diode/Switch Spacer Thickness	Cu	mm	0.20	3.00
Collector Plate Thickness	Cu	mm	0.05	3.00
Emitter Plate Thickness	Cu	mm	0.05	3.00
Collector Insulator Thickness	Dielectric Thin Film	mm	0.25	1.00
Emitter Insulator Thickness	Dielectric Thin Film	mm	0.25	1.00
All Joint Thicknesses (5 separate params.)	Solder	mm	0.05	0.10

Parameters	
Junction Temperature	**Maximum Temperature ($T_{j, max}$)**
	Change in Temperature (ΔT_j)
Operational Temperature for Layers	Dielectric Temperature (T_d) Joint Temperature (T_{jt})

Devices



Package

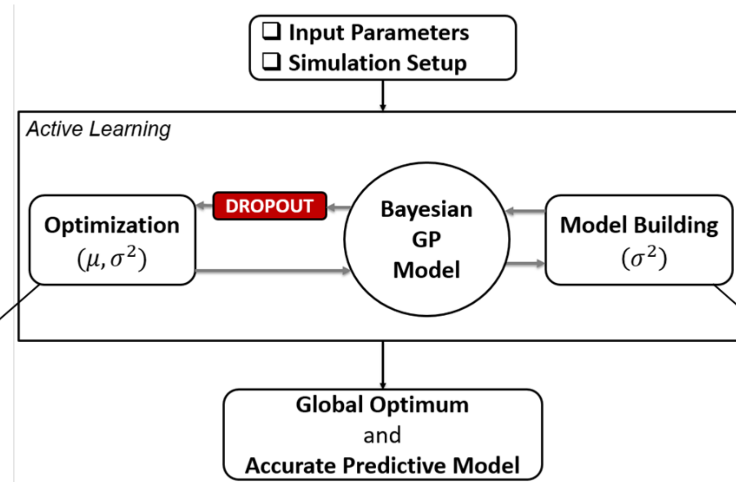


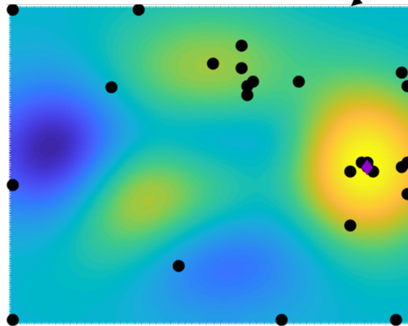
Objective:

1. Find thickness that minimizes T_{jmax}
2. Perform sensitivity analysis to determine which parameter(s) has more effect.

in minimum CPU time

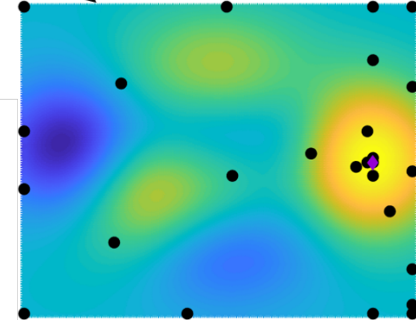
Bayesian Active Learning using Dropout (BALDO)





Design space explored for only for optimization

H. M. Torun et al, EPEPS'18

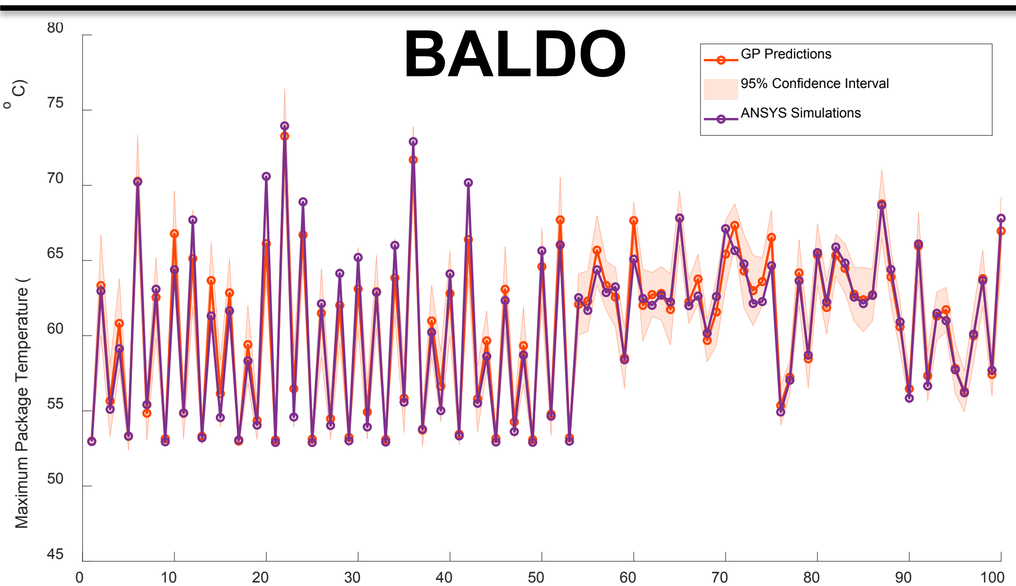


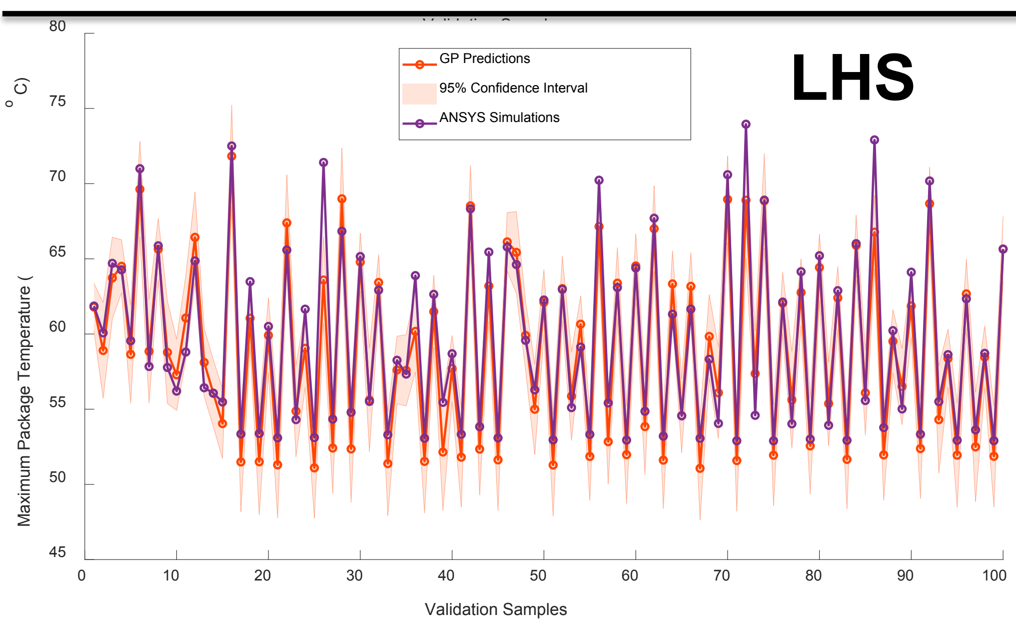
Design space explored for both optimization and model building

- Bayesian Optimization can find minimum temperature but can't build an accurate model.
  - Need the model for sensitivity analysis.
- Is there a way to optimize AND build accurate model at the same time?
- Alternate between optimization and model building at every iteration.
  - **Better Model** → Avoid Local Optima → Faster Optimization
  - **Optimization** → Learn Saddle Points → Higher Model Quality

Complementary Objectives

Results: Model Accuracy



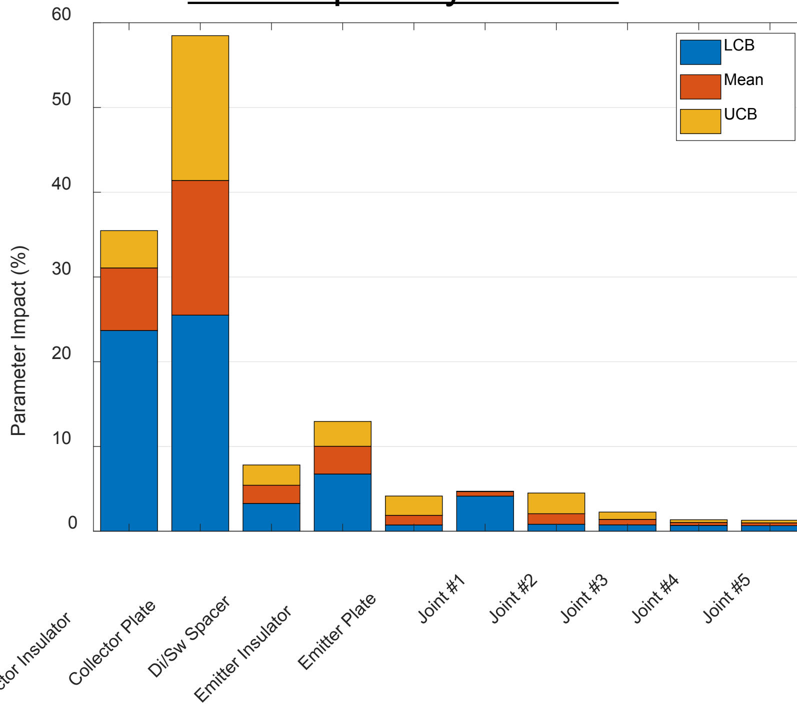


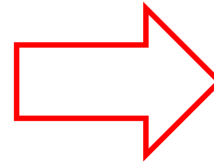
Max. junction temperature with original DENSO package dimensions: **57.4°C**

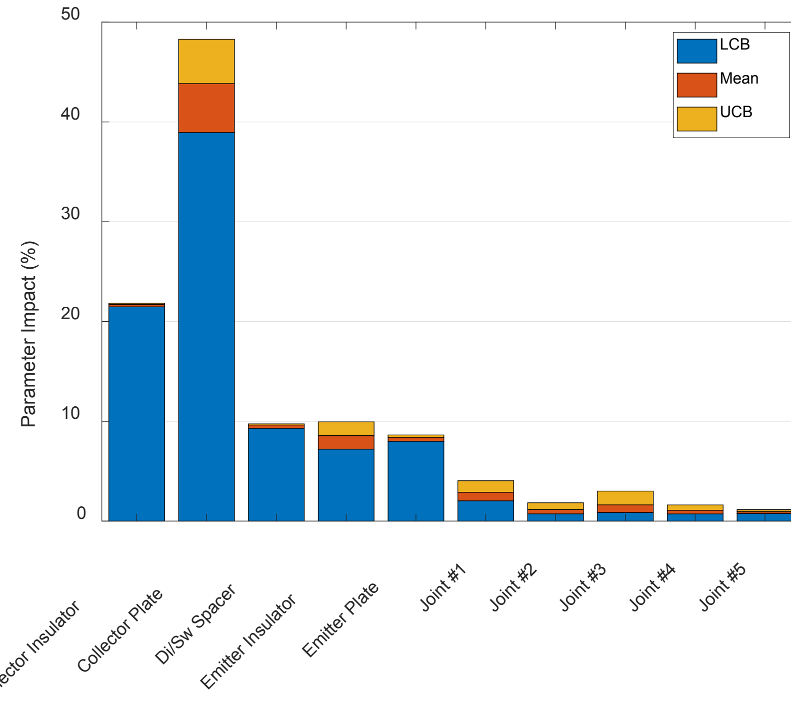
	LHS	BALDO
Norm. Mean Squared Err.	7.76%	4.94%
Max. Junction Temperature	54.0°C	52.9°C
Av. Absolute Error	0.897°C	0.687°C
Max. Width of Confidence Interval	1.976°C	1.703°C

- Performance of models using data collected by BALDO and Latin Hypercube sampling is collected.
- For both methods, 50 samples are used for training and 100 for testing.
- Performance gain through BALDO is expected to be more when the non-linearity increases.
  - Ex: multi-physics environment.

Results: Sensitivity Analysis







- Sensitivity analysis is obtained as a by-product (free!) of active learning.
- As the data is scarce, confidence bounds over parameter weights are necessary.
  - Bayesian training of the GP allows to do so.
- As more data is added, confidence bounds shrink.
- Collector Plate thickness and Collector Insulator thickness has the largest impact.

Schedule

Next steps:

- Machine learning: handling categorical parameters (material choices and their parameters, insulator technology)
- Multi-physics environment: fully parametrized layout (XY plane), mechanical and electrical solves

	2019	2020				2021		
	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3
Parametrization								
Multiphysics Environment								
Initial Pass of Thermal Solve								
Expansion of Thermal Solve								
Thermomechanical Solve								
ML based optim. on continuous params								
Extend to Categorical Parameters								
Material & Geometry Co-Optimization								
Extend to Conditional Parameters								
Package Architecture, Material, Geometry Co-Optimization								

Multi-Physics Simulation Environment
ML Model Development

Summary

- Very recently started project.
- BALDO was used for the simplified problem of minimizing max. junction temperature of DENSO structure.
- Critical elements in the DENSO structure were highlighted for the most thermal impact (collector plate).
  - Along with confidence bounds.
- Next step is to extend thermal model to multi-physics model and perform material & geometry co-optimization.
- The ML methodology developed throughout the project will enable us to generate unseen package architectures.

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Back-Up Slides

Complexity of Multiphysics Problem

Coupling of Models

Converter Topology

Circuit model (Spice)

- Component libraries for power devices & passive components
- Control strategy

Power losses in active devices (conduction & switching) / mission profile

Power card Architecture / Layout / Materials

CURRENT FOCUS

Package Parasitics (R, L, C)

ML

Package Parasitics (ANSYS Maxwell)

Device Thermal Mapping

Thermal Solve (ANSYS)

Thermal Mapping

Mechanical Solve (ANSYS)

Stresses / Strains