Multi-Objective Optimization of Solar Cells Thermal Uniformity Using Combined Power of ANSYS Multi-Physics, modeFrontier and eArtius

Vladimir Kudriavtsev, Terry Bluck (Intevac)
Vladimir Sevastyanov
(eArtius, Irvine, CA)

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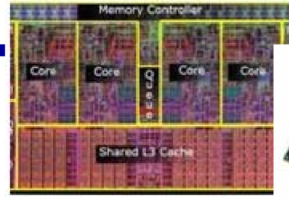
Current Computational Design Process



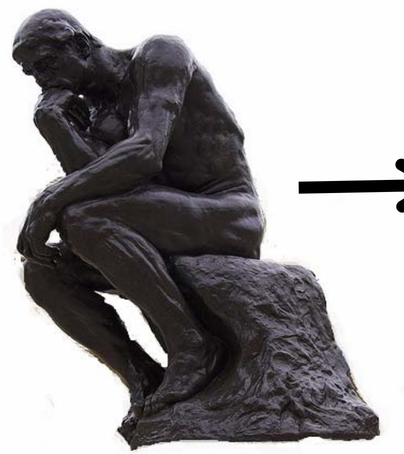
8 threads i7 CPU

Computer

240 cores TESLA Graphic Processing Unit GPU (x2)

fastest component

and grows exponentially faster



Human Thinking

and Analysis

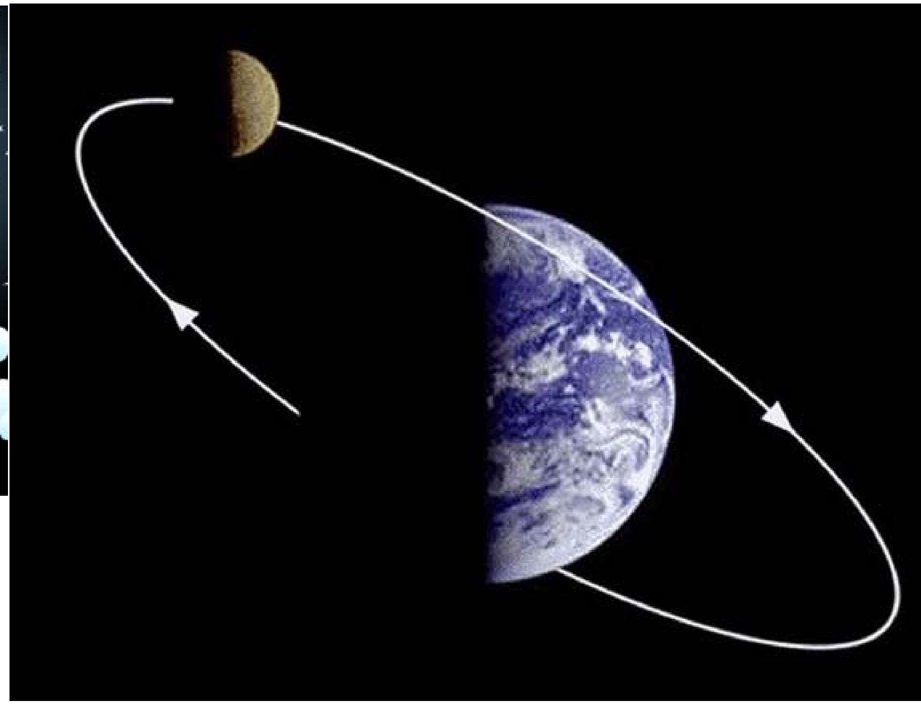
slowest component

(meetings, reviews, alignments, cancelations)

Ingenious

Solutions

Morning after Effect



10 times CPU speed improvement

10 hours overnight job
or
1 hour overnight job

Makes no difference
at 8 AM in the morning

Why Optimization by Computer?

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Human can not match computer in repetitive tasks and consistency. Assuming computational problem takes 30 minutes of CPU time, then in one day (between 8AM to 8 AM) computer is capable of producing 48 design evaluations, with 144 designs completed in just 3 work days.

Coupled with multi-processing capability of i7 workstation this number can easily be multiplied by factors ranging from two to six.
Computer will work during the weekend; it will work when user is on vacation, on sick leave or on business trip.

-"Nothing to run" as single user mental bottleneck is reached, computer resource is underutilized, software is idle.

Personal "super computer" cost is now inconsequential for the bottom line.

Software cost sky-rocketed, and its ROI and utilization efficiency is now most important.

Computer needs algorithmic analogy of "human brain" to self-guide solution steps.

New Paradigm

New paradigm of <u>multi-objective computational design</u> is now being born.

No longer designer needs to approach it through “trial-and-error” simulations, but can rather use “artificial intelligence” of optimization method to automatically seek and to find best combination of input parameters (design). Depending on problem size (CPU time) this process can take from minutes to weeks.

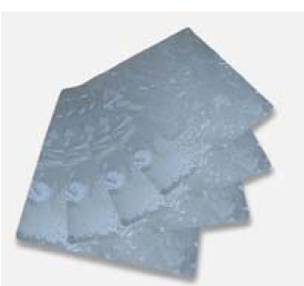
However, now engineer can view tens and hundreds of possible solutions, automatically singling first truly best designs and then evaluate design trade-offs between conflicting objectives (Pareto Frontier).

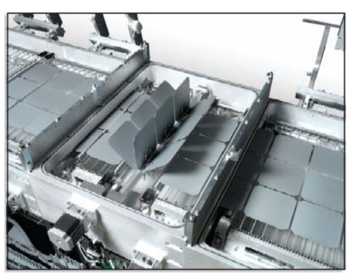
Heating Challenge to Address

LEAN SOLAR™
A Revolution in Value for the Solar Industry

Great number of companies and technologists in Silicon Valley are now focused on developing lower-cost processing methods and capital equipment to manufacture solar cells. It is typically done through a variety of high temperature thermal processes, where temperature uniformity is the most critical factor.

Using ANSYS Workbench we developed lamp heating surface-to-surface thermal conduction-radiation model for simultaneous transient multi-step heat-up of silicon substrates. Lamp locations, lamp to substrate distances, lamp dimensions, lamp power and its distribution are being optimized to achieve industry standard ±5 degrees thermal uniformity requirement.





http://www.intevac.com/solar-process-sources

Problem Formulation

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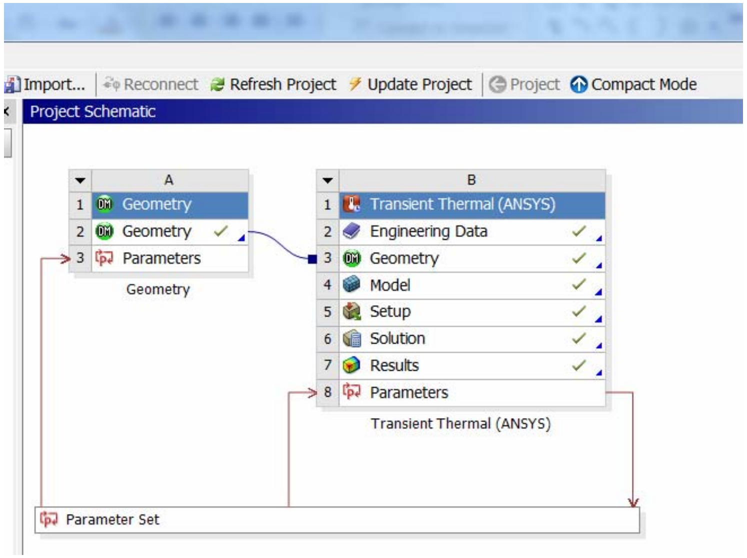
Minimize thermal variation across single substrate and across a group of substrates during radiant heating stage (TempDiff)

Operate in required process temperature window, T-dev1<Top<T+dev2

Optimization Formulation

ANSYS WB Formulation:



Top=400 deg.C

***min* (TempDiff)**
***min* abs(Tmax-Top) & *min* abs(Tmin-Top)**

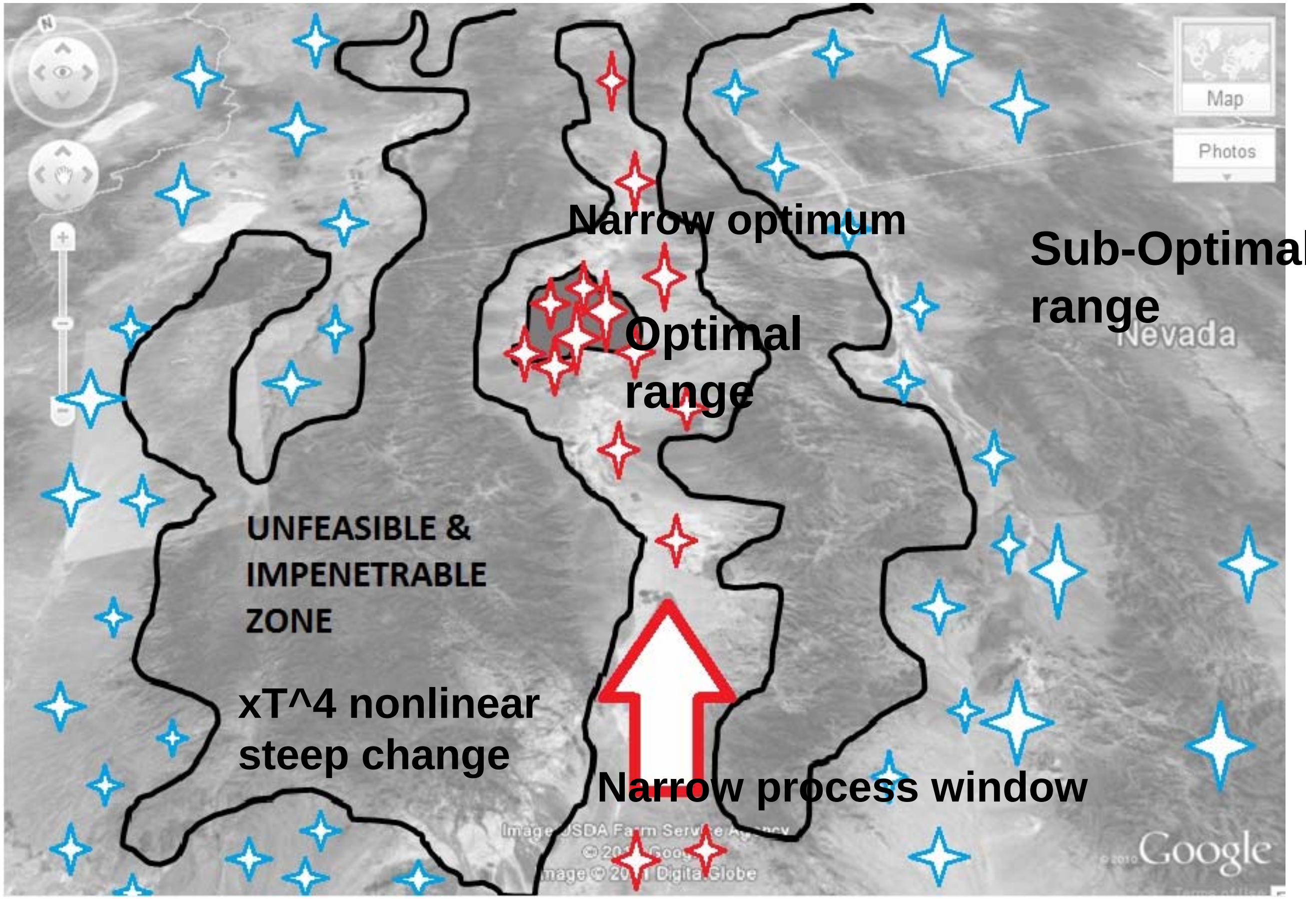
Constraints to determine design feasibility:

***T<Tmax.constr* & *T>Tmin.constr*, where**

Tmin.constr= Top-dev1*, *Tmax.constr=Top+dev2

If dev1 and dev2 are small, then optimization problem is very restrictive.

Problem Analogy – Hidden Valley in the Mountains



Gradient method requires path, to enter narrow optimal range (due to nonlinearity) it requires guidance or coincidence. Guidance comes from the previous history (steps taken before, gradients) and coincidence from DOE or random mutations.

Mode Frontier and eArtius Roles

In our study we used modeFrontier as optimization enabling (Scheduler) and statistical data post-processing tool and eArtius multi-objective optimization methods plug-in tool to guide continuous process of selecting better input variables to satisfy multiple design objectives.

This process follows "fire and forget" principle and relies on combination of self-guiding gradient methods with genetic selection (crossover and mutation). Algorithm automatically use current results to best select inputs for the next design decision step. Gradient based computer thinking combines advantages of precise analytics with human like decision making (selecting roads that lead to improvement, avoiding weak links, pursuing best options, connecting dots). Genetic component guides selection and allows to jump out if local improvements can not be found.

Thermal System Optimization Task Formulation

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Objectives:

$Minimize+ \quad TempDiff$
$Minimize+ \quad SubMax400$
$Minimize \quad SubMin400$

Constraints:

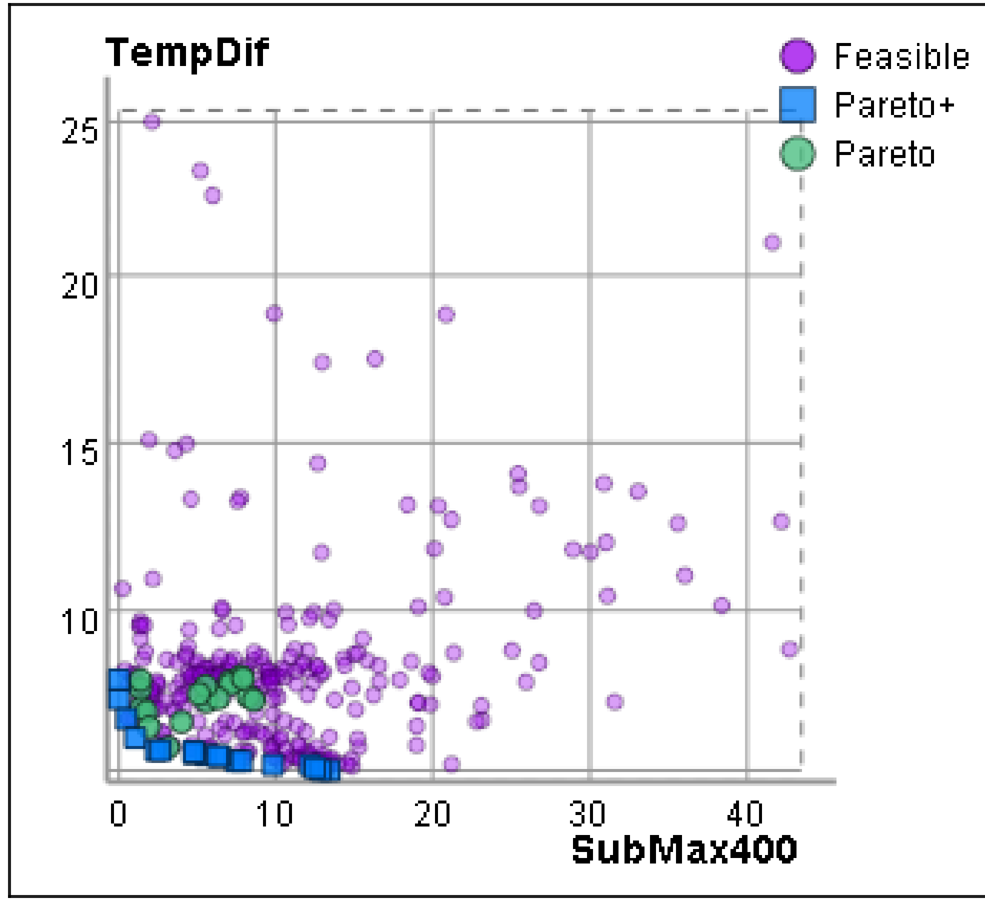
$Lower < 35$
$Tdiff12 < 35$
$Upper < 45$

Need to carefully consider

Design Variables:

$Height \in [-0.055, 0.035]$
$SubMinus \in [-0.015, 0.020]$
$SubPlus \in [-0.015, 0.030]$
$T2 \in [735, 940]$
$T2 \in [735, 940]$

Minimize+ – preferable objectives
Minimize – regular objective



278 feasible designs *of 317 evaluations*
18 Pareto+ designs *of 35 Pareto optimal designs*

Optimization Flow Chart in ModeFrontier

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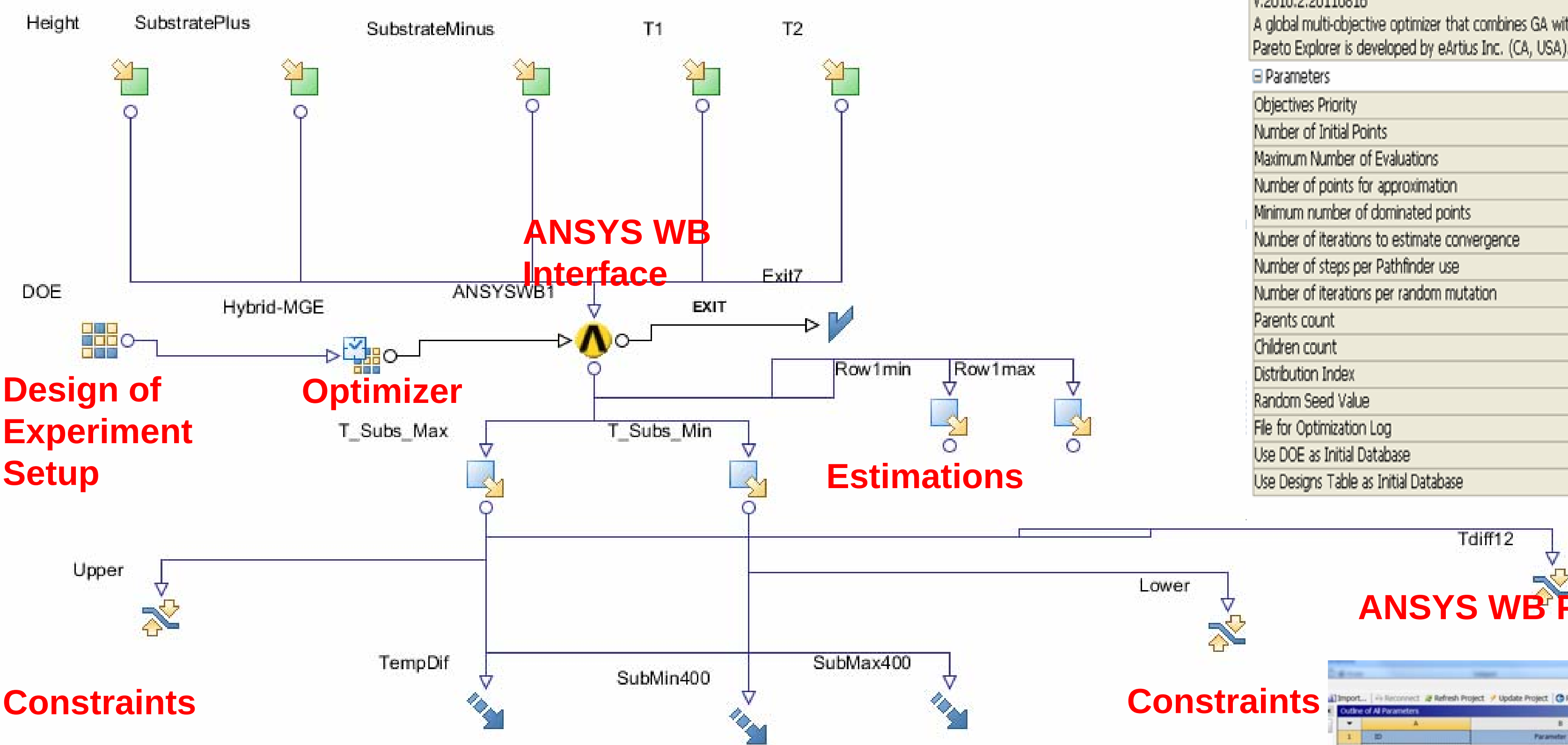
Inputs (from ANSYS WB parameters):



Objectives- to minimize

Optimization (HMGE) Setup

Hybrid-MGE

Hybrid-MGE (HMGE)
v.2010.2.20110816
A global multi-objective optimizer that combines GA with gradient-based technique.
Pareto Explorer is developed by eArtius Inc. (CA, USA).

Parameters

Objectives Priority		
Number of Initial Points	[8,256]	34
Maximum Number of Evaluations	[1,9999]	7000
Number of points for approximation	[7,30]	12
Minimum number of dominated points	[0,1000]	0
Number of iterations to estimate convergence	[0,9999]	40
Number of steps per Pathfinder use	[0,9999]	5
Number of iterations per random mutation	[0,9999]	3
Parents count	[4,9998]	8
Children count	[4,9998]	4
Distribution Index	[0.0,100.0]	0.5
Random Seed Value	[0,9999]	11
File for Optimization Log		E:\mf2011\tryou
Use DOE as Initial Database		☐
Use Designs Table as Initial Database		☑

ANSYS WB Parameters:

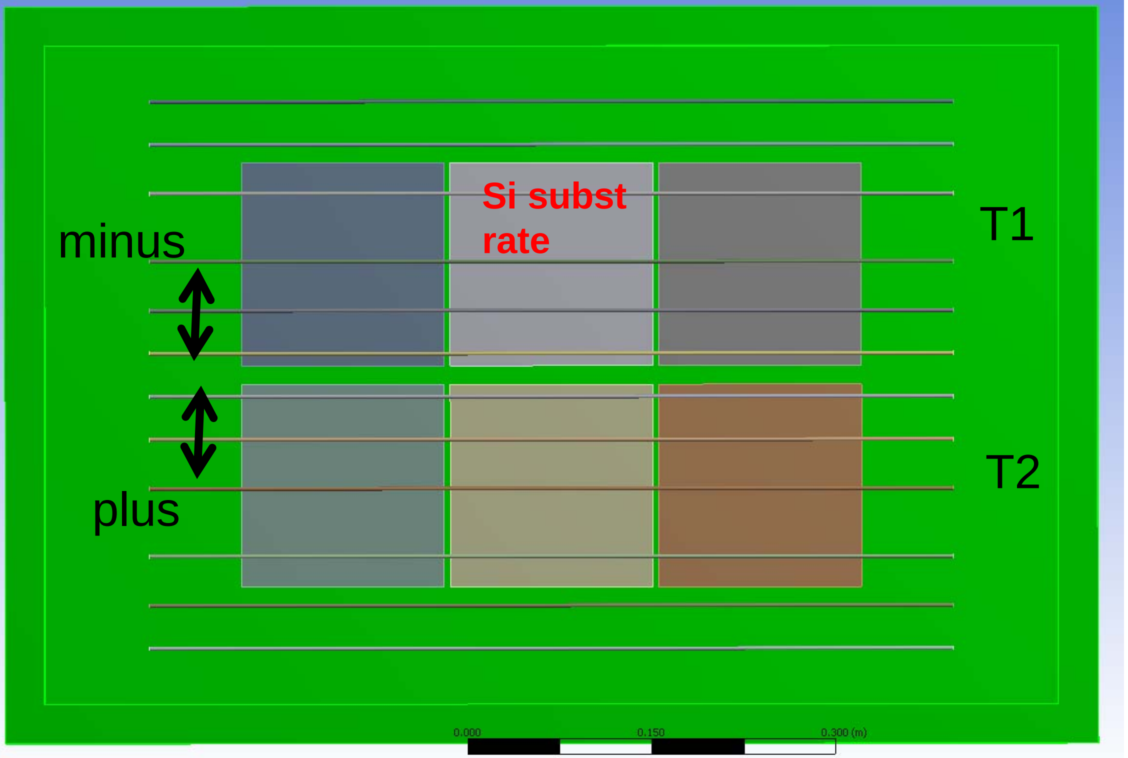
Import... | Reconnect | Refresh Project | Update Project | Return to Project | Compact Mode

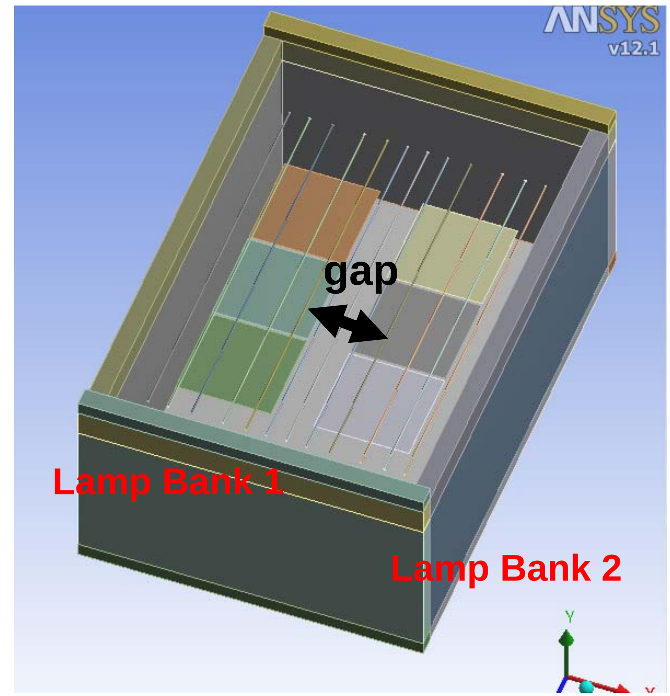
Outline of All Parameters

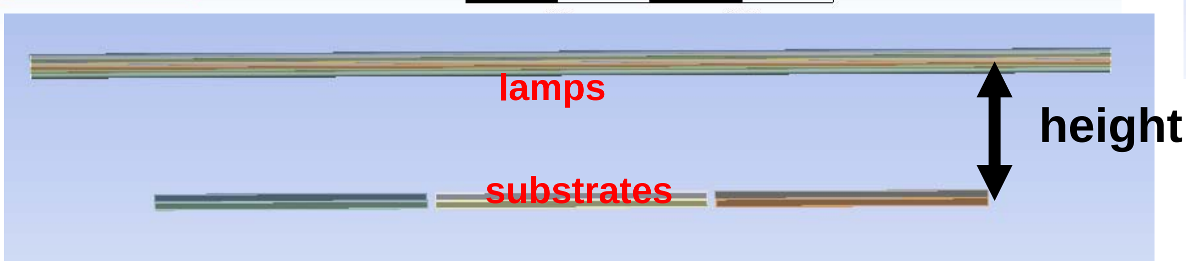
	A	B	C	D
1	ID	Parameter Name	Value	Unit
2	Input Parameters			
3	P2	Plane16move.FD1	0	
4	P5	Plane20row1plus.FD2	0	
5	P6	Plane18row2plus.FD2	0	
6	P7	Temperature Magnitude	900	C
7	P8	TemperatureR1 Magnitude	900	C
*	New input parameter	New name	New expression	
9	Output Parameters			
10	P9	TemperatureR1 Maximum Maximum Value Over Time	268.9	C
11	P10	TemperatureR1 Maximum Minimum Value Over Time	249.32	C
12	P11	TemperatureR2 Maximum Maximum Value Over Time	410.98	C
13	P13	TemperatureR2 Maximum Minimum Value Over Time	394.5	C
14	P14	Output Parameter	16.484	K
15	P15	Output Parameter	19.574	K
*	New output parameter		New expression	
17	Charts			

Problem Parameters – Geometry and Temperature

<Tempdiff> =Tmax-Tmin
between 3 substrates



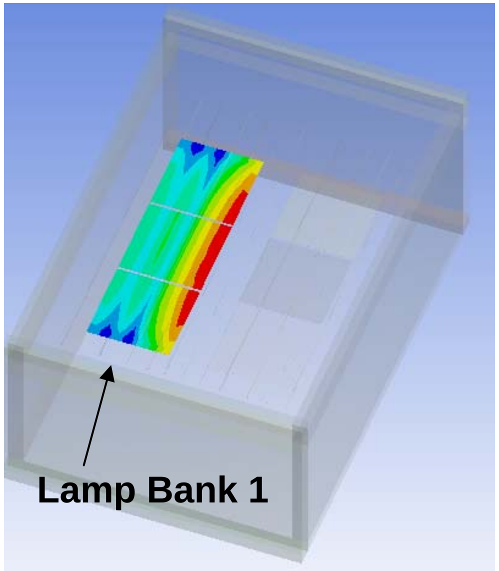




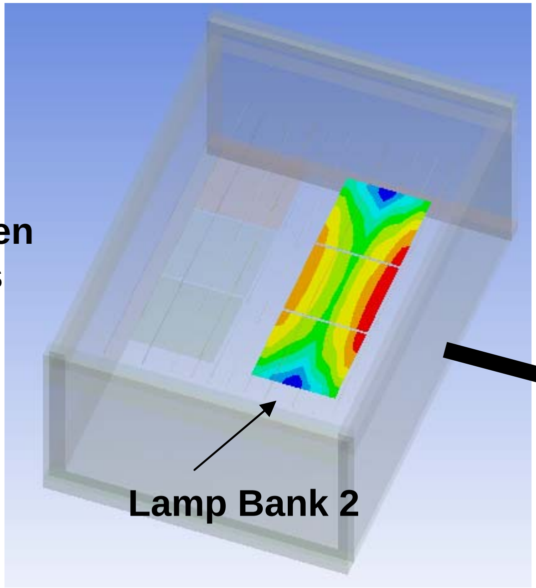
T1-radiation temperature of first lamp array;
T2-radiation temperature of second lamp array;

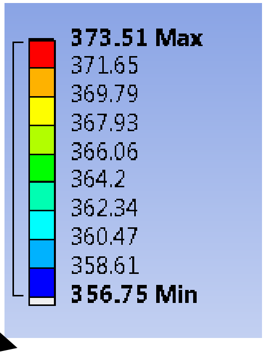
T1,T2 –radiation temperatures, control heat flux from lamps.

Thermal Heating (Radiation) Solution

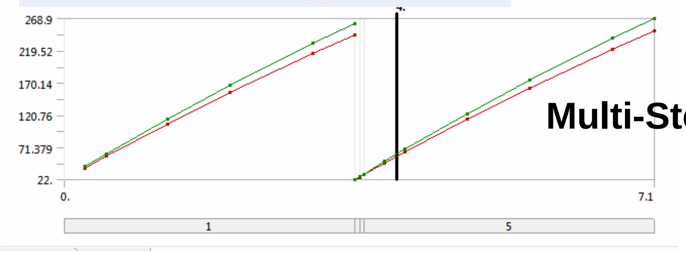


Interplay between
two lamp arrays

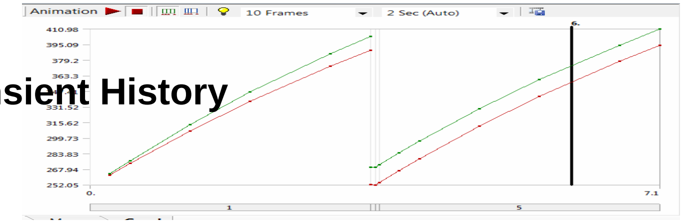




Substrate Motion
Direction



Multi-Step Transient History



Transient Heating Scenario: **Row1 of substrates is first heated by Lamp Bank1, then these Substrates moved to Lamp Bank2 and get heated again till desired Top=400 deg.C is reached. Simultaneously, new substrates with T=Tambient populate Row1 and get heated. Thus, Row1 heats from 22 to 250 deg.c and Row 2 from 250 to 400 deg.C.**

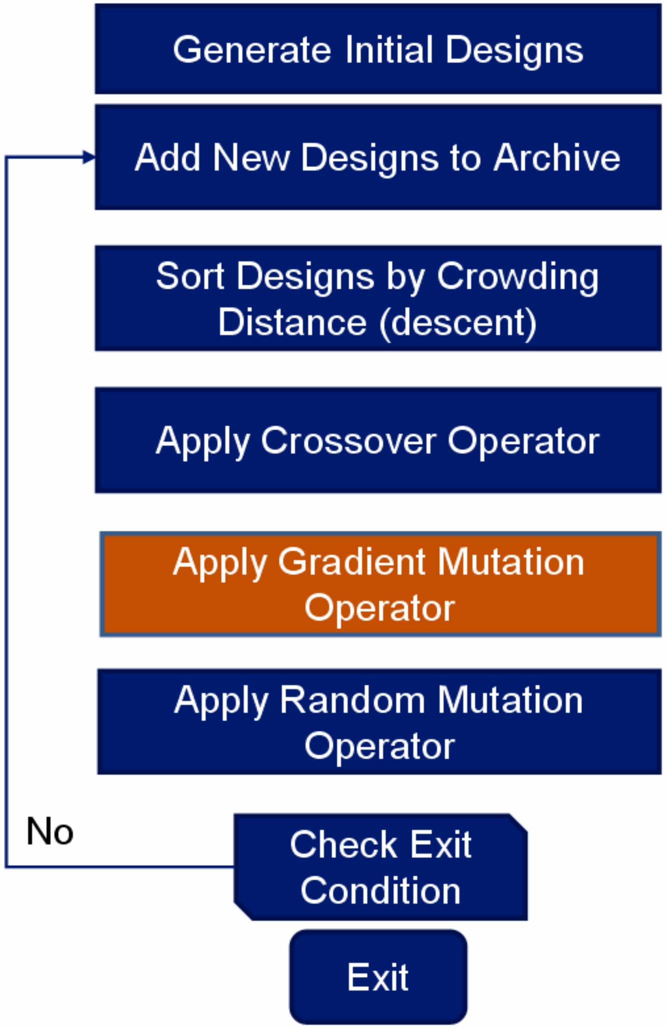
at time t=3.5 sec Row1 T is reset at 22 deg.C; Row2 T is reset at 250 deg.C.

at time t=0 sec Row1 T is set at 22 deg.C; Row2 T is set at 250 deg.C.

Hybrid Multi-Gradient Explorer (HMGE)

New Hybrid Multi-Gradient Explorer (HMGE) algorithm for global multi-criteria optimization of objective functions considered in a multi-dimensional domain is utilized in this study. This hybrid algorithm relies on genetic variation operators for creating new solutions, but in addition to a standard random mutation operator, HMGE uses a gradient mutation operator, which improves convergence.

Thus, random mutation helps find global Pareto frontier, and gradient mutation improves convergence to the Pareto frontier. In such a way HMGE algorithm combines advantages of both gradient-based and Genetics-based optimization techniques: it is as fast as a pure gradient-based algorithm, and is able to find the global Pareto frontier with robustness similar to genetic algorithms (GA).



www.eartius.com

Dynamically Dimensioned Response Surface

DDRS Method is a **fast and scalable algorithm for estimating gradients**

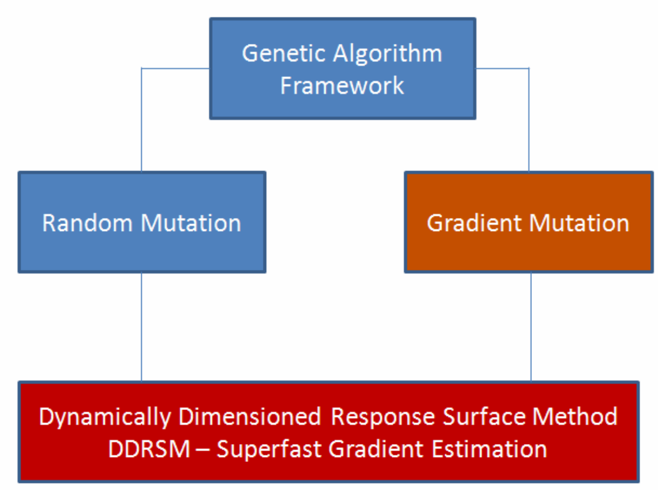
DDRSM can be used as an element for designing any gradient-based optimization algorithms, including hybrid algorithms.

How DDRSM operates:

- Automatically determines the most significant design variables for each response variable separately
- Builds local approximations for each response based only on the most significant design variables
- Estimates gradients analytically based on local approximations
- Repeats the above sequence on each optimization step

DDRSM Benefits:

- Equally efficient and accurate for any task dimension
- Requires just 0-7 model evaluations regardless of task dimension
- Fast— it builds a local approximation in 10-30 milliseconds
- Automatic and hidden from users
- Eliminates necessity in global response surface methods
- Eliminates necessity in a sensitivity analysis



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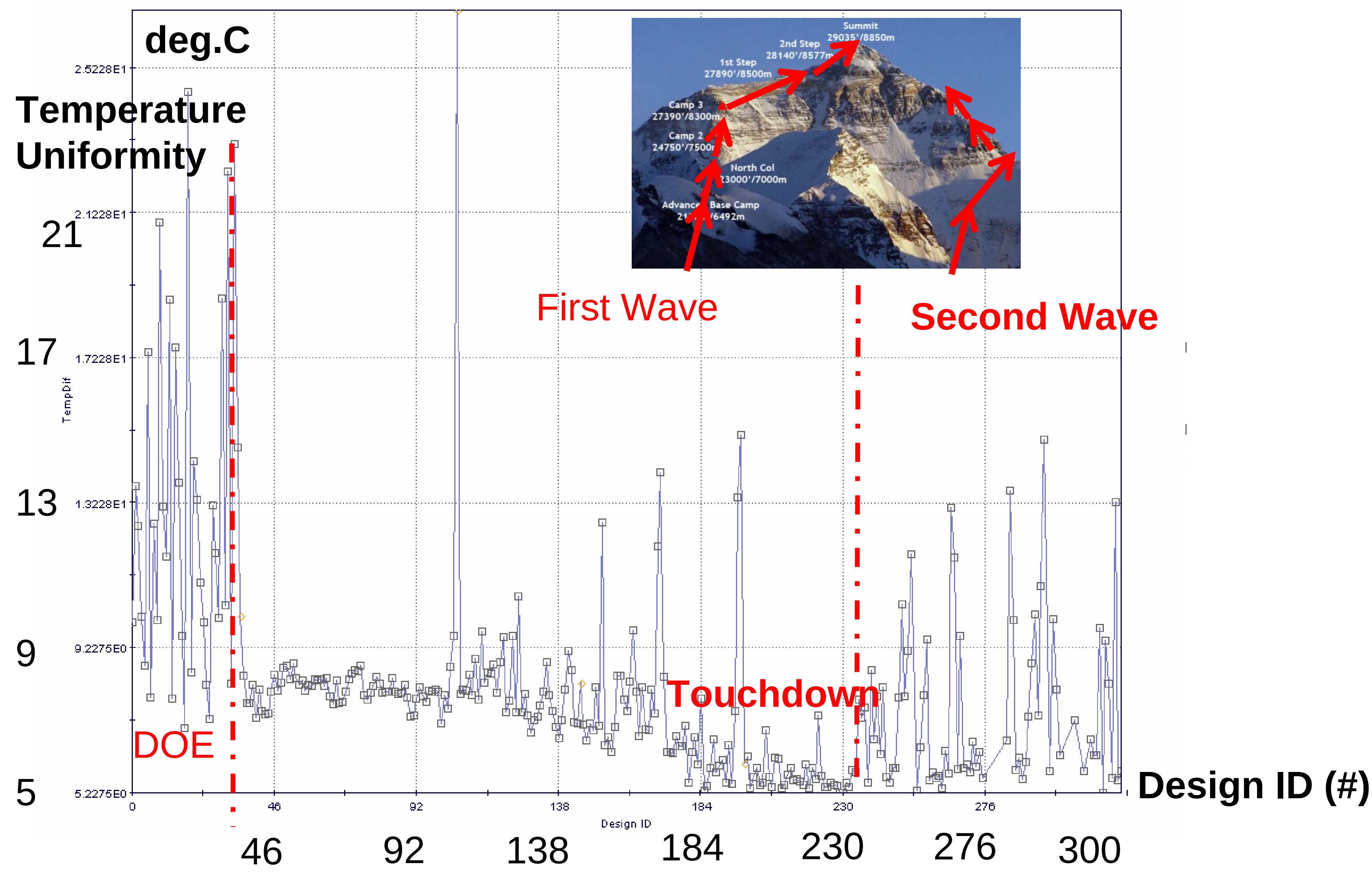
"Fire And Forget" Solution Process - HMGE



HMGE Optimization of Temperature Difference

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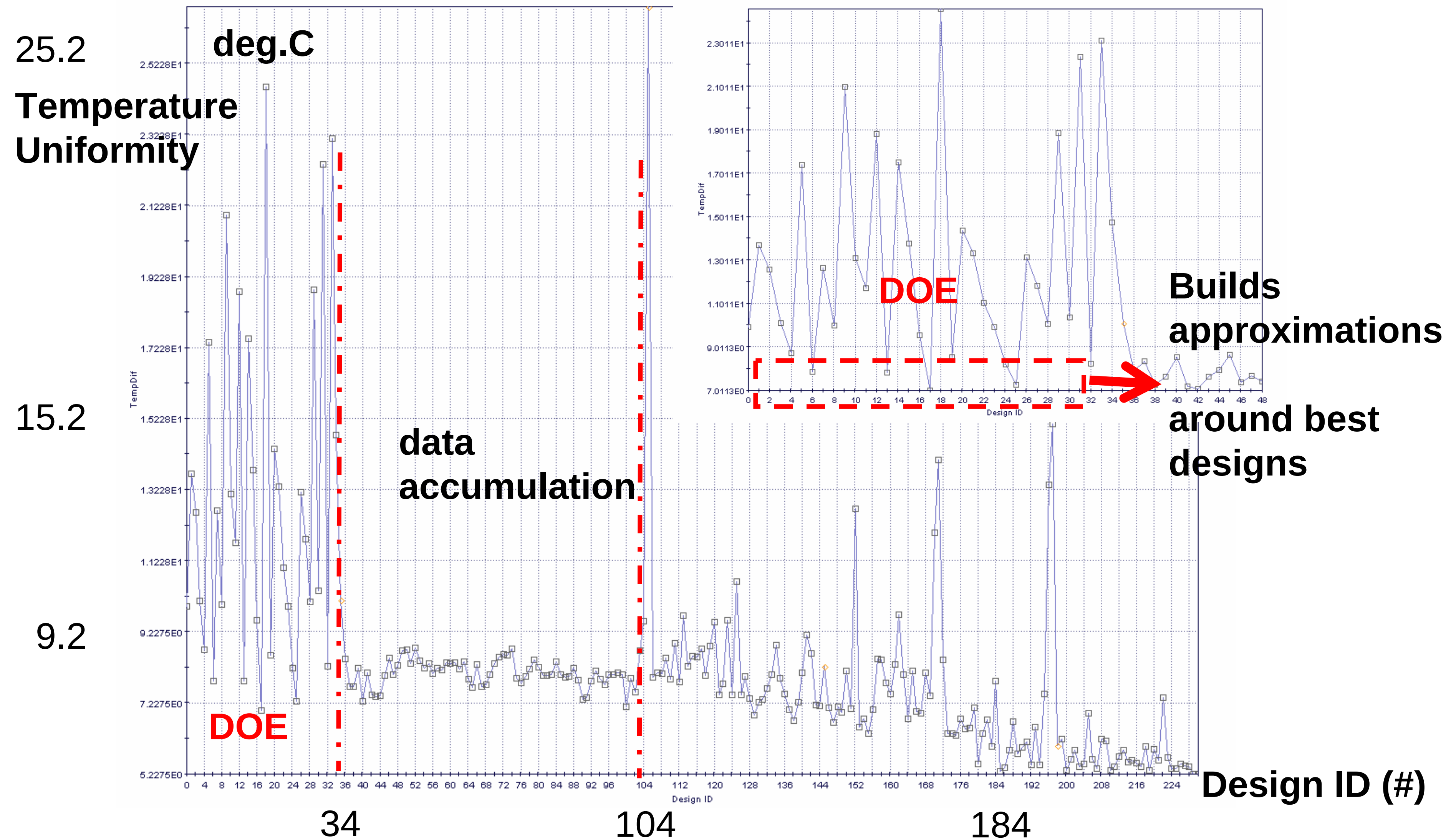
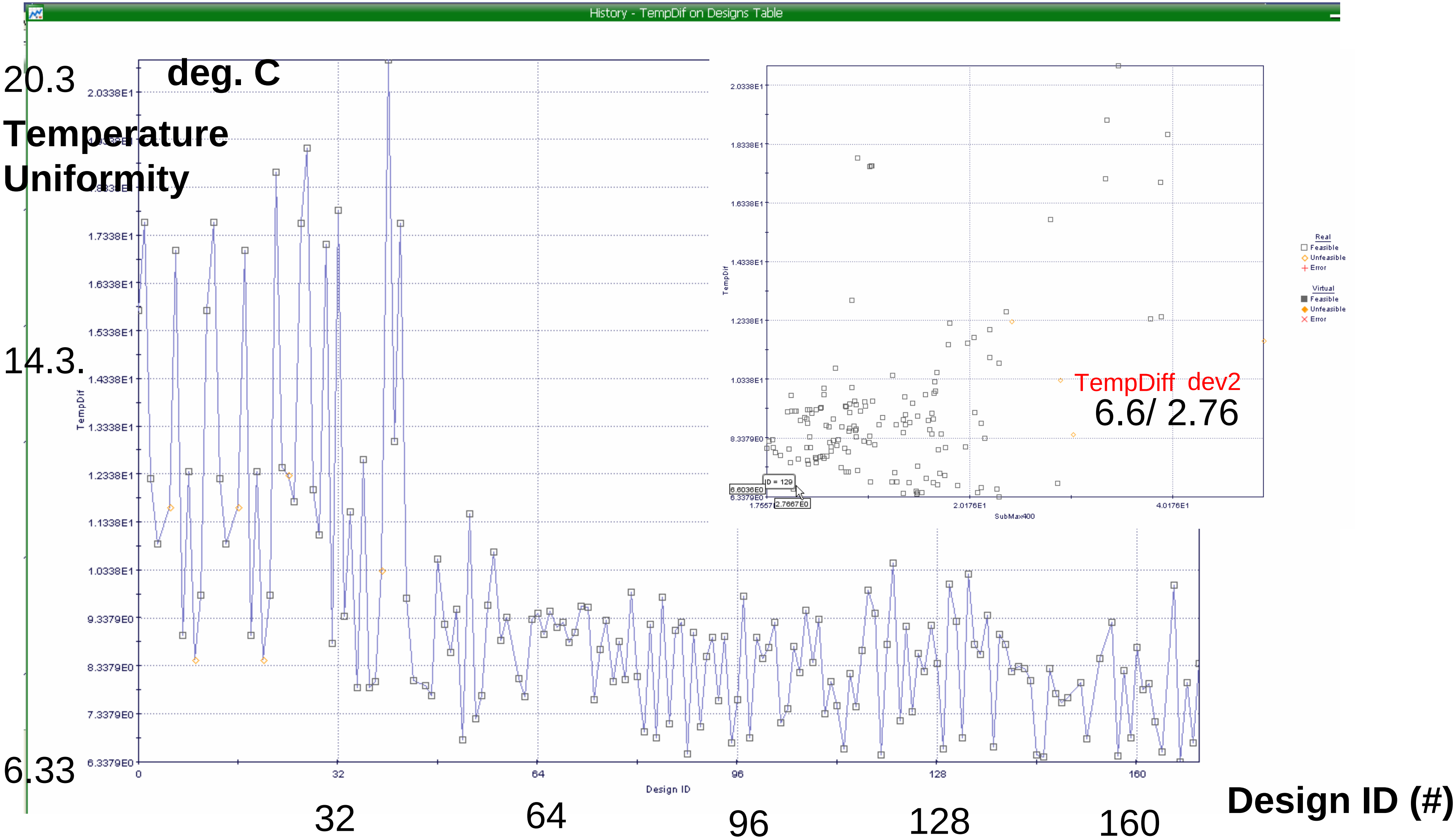


Optimization Using NSGAII modeFrontier



Optimization Solution: Pareto Front

Plotted using modeFrontier

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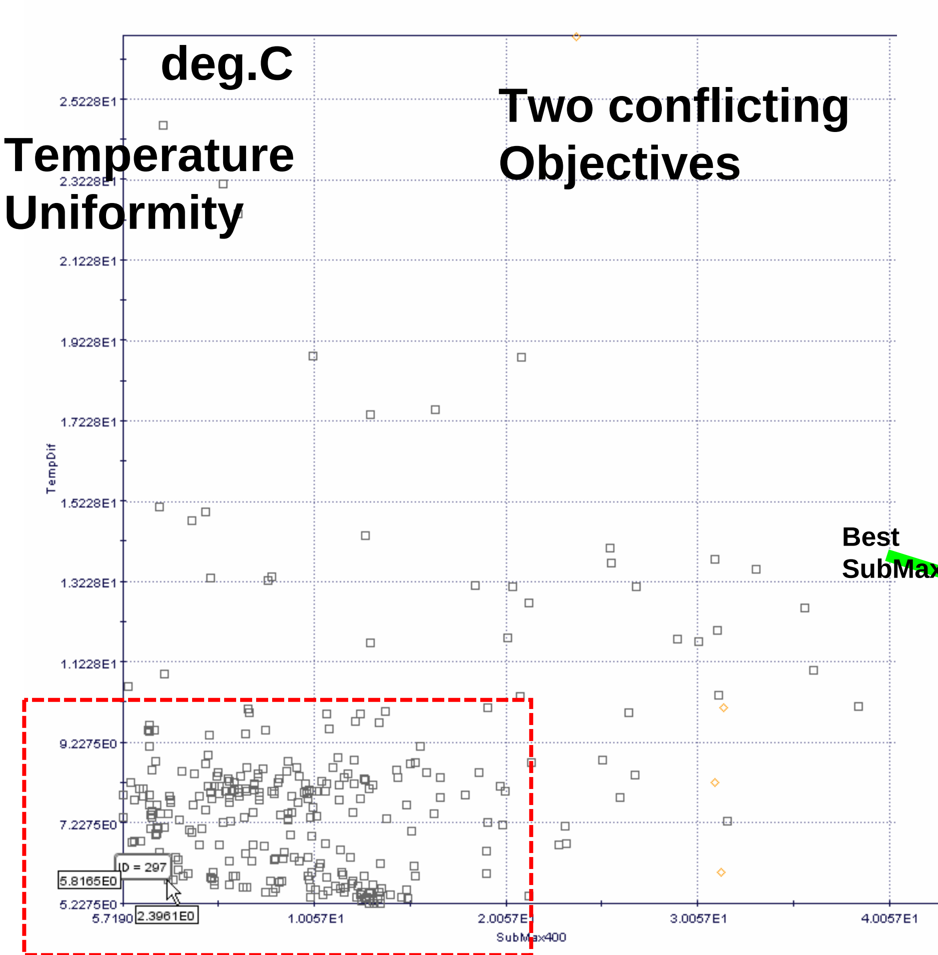
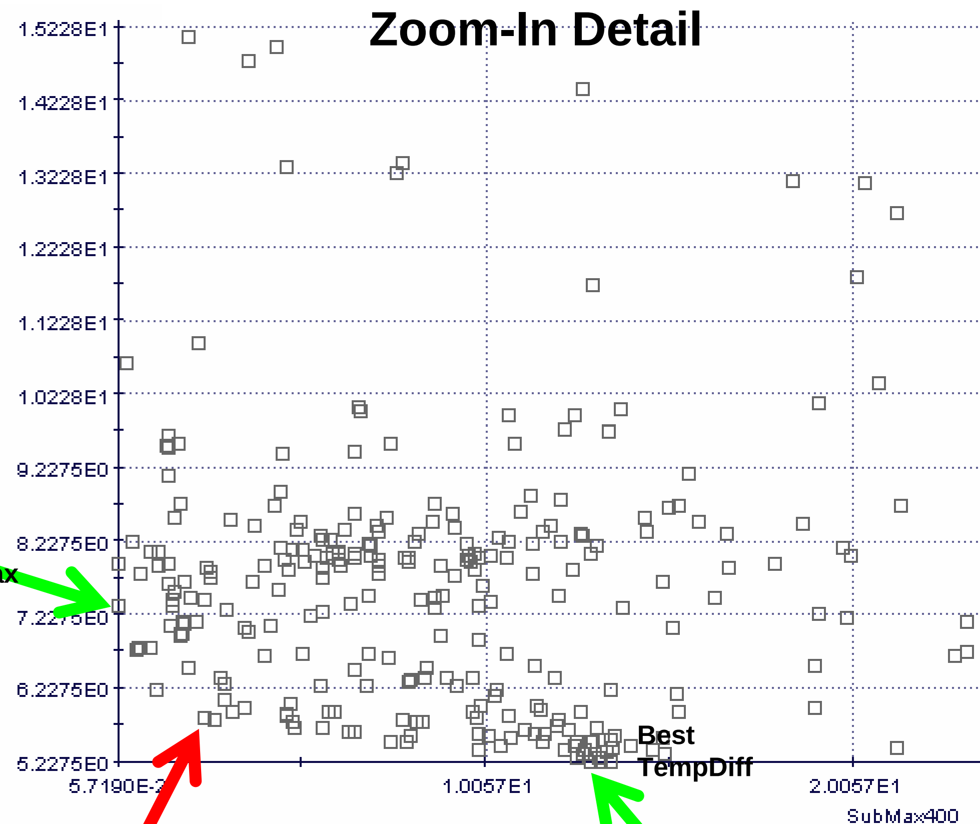
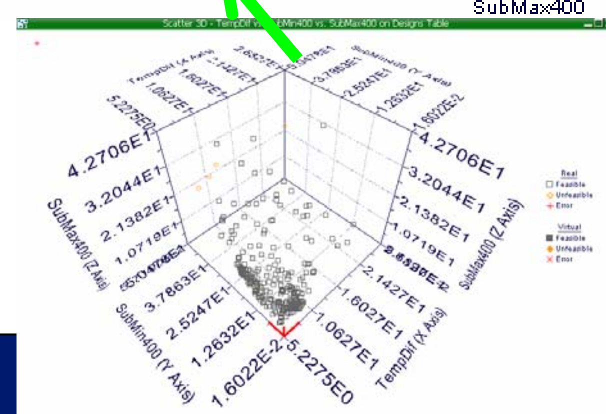


Maximum Temperature, (T-Tmax)





Multi-Design Decision Making in mFrontier

Plotted using modeFrontier

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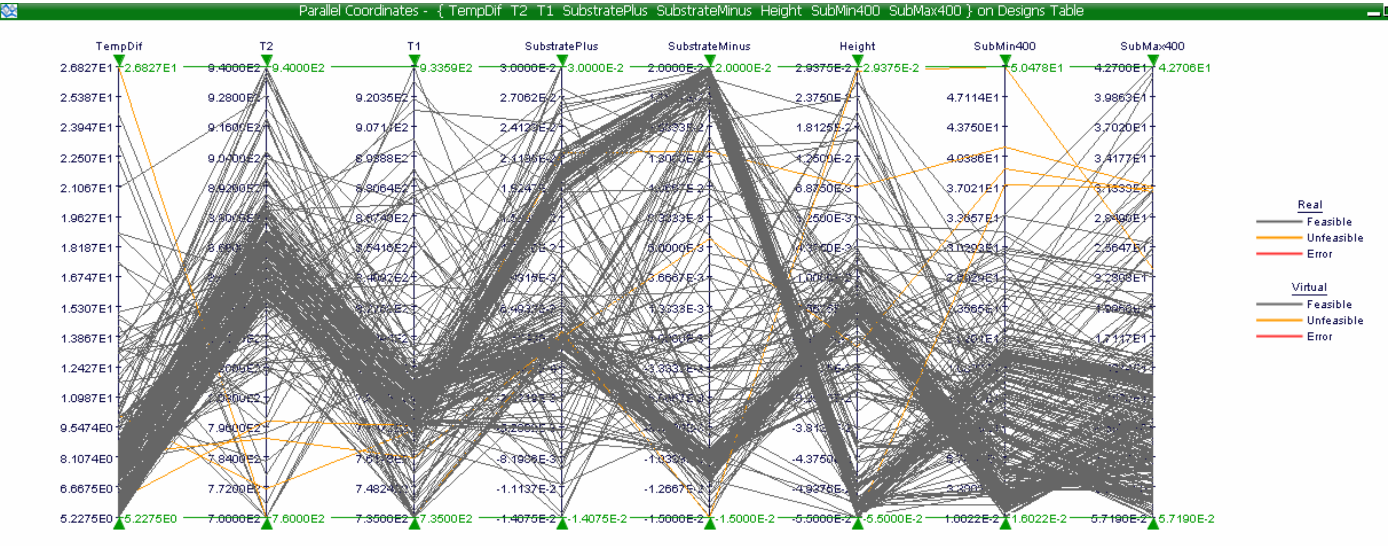
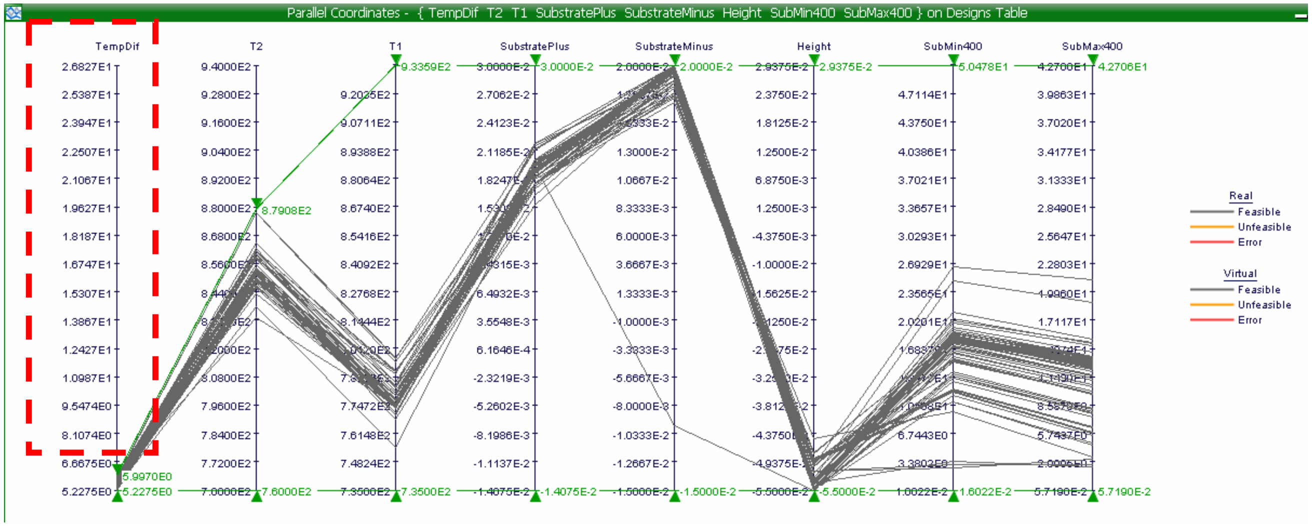


MDDM—initially very cluttered and confusing



Tempdiff is narrowed to Less than 6 deg.C and suddenly way more clarity

Best Designs Selected -MDDM

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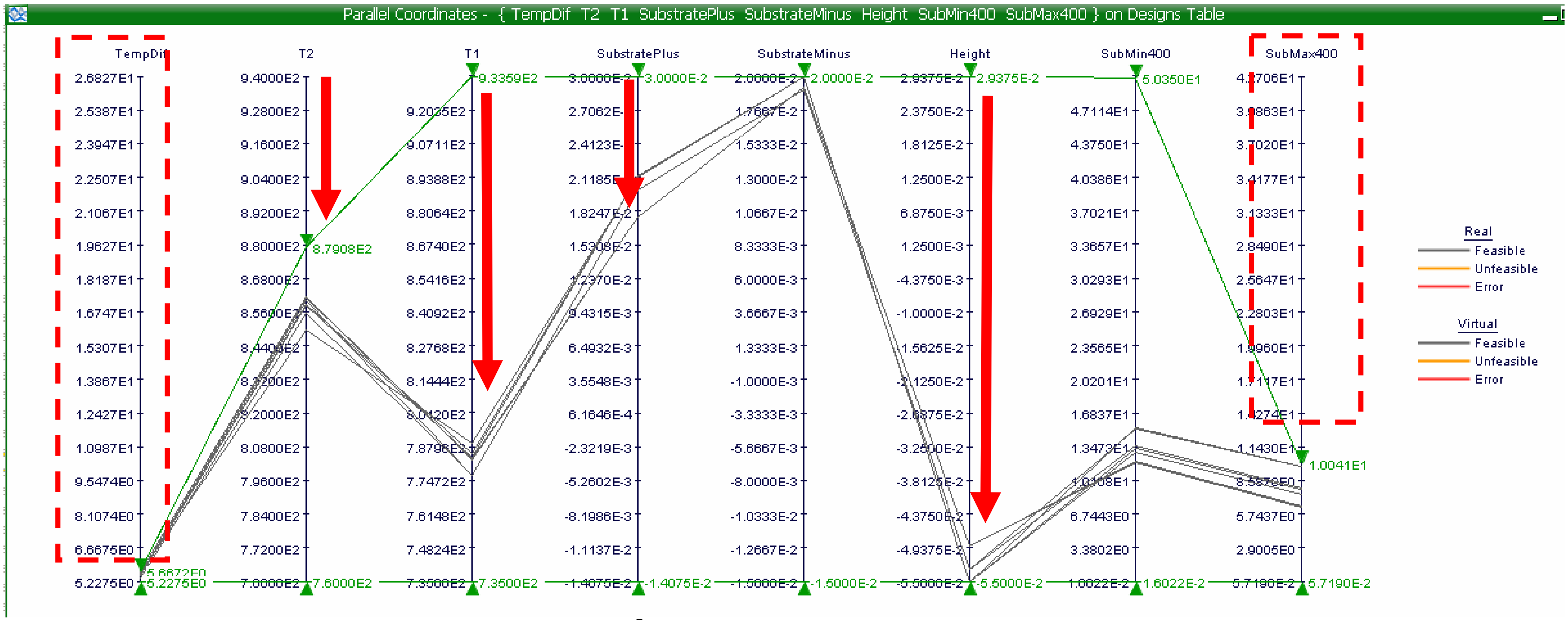
<u>So, to improve design we had to:</u> lower T2; lower T1 below T2; move substrates of second row outward, Keep substrate for first row same position, drop substrates ~0.05 m away from lamps and base position.

Plotted using modeFrontier

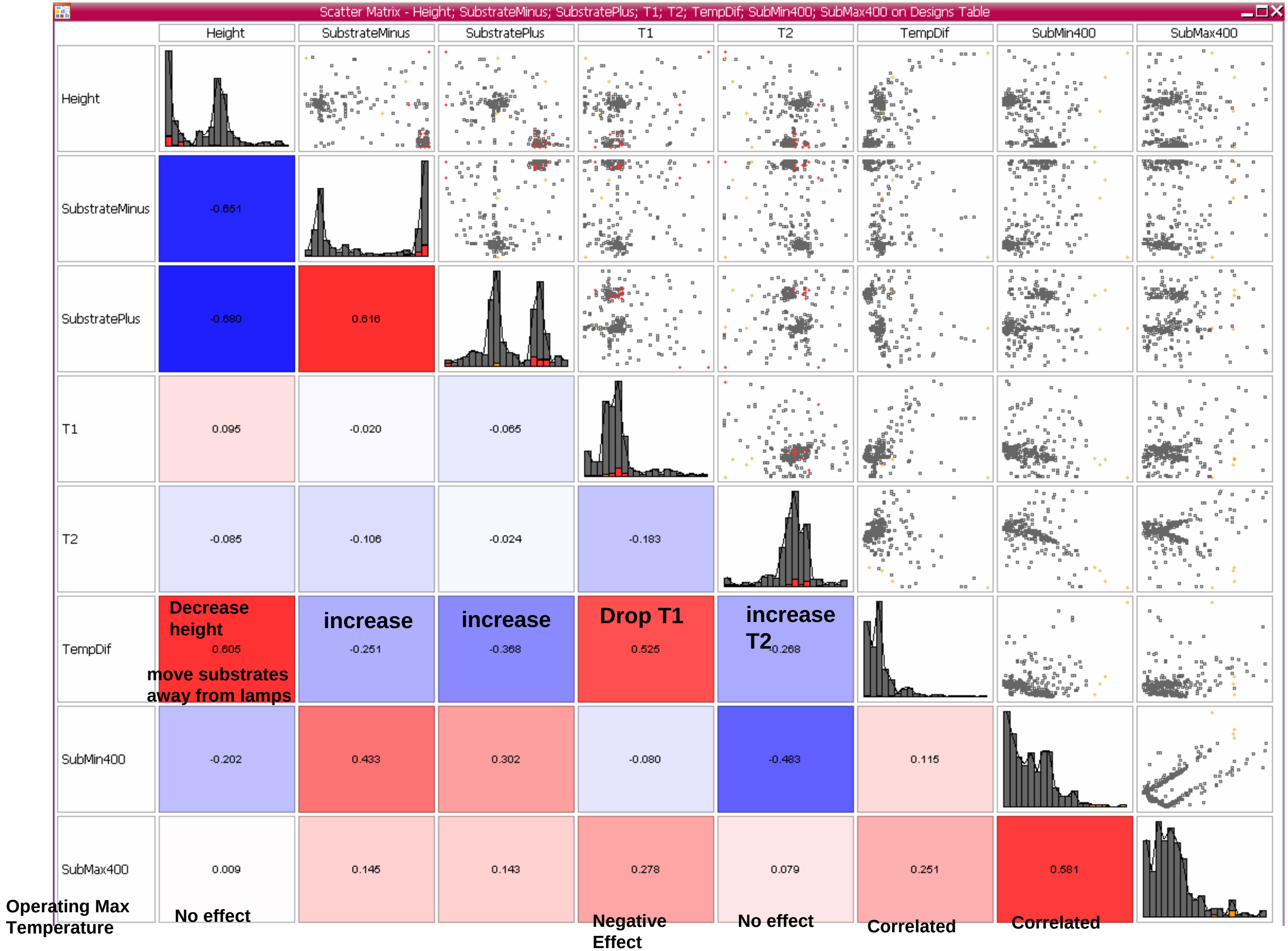


row2 **row1**

<Tempdiff> is narrowed to less than 6 deg.C and allowable deviation from maximum temperatuire reduced to 10 deg.C. Only several acceptable designs are left to consider.

Scatter Optimization Summary Matrix

Plotted using modeFrontier



Red color affects positively;
Blue color-negatively.
Increase in Tdiff means that design is worse, as we want to minimize TempDiff.

SubMax400 – deviation above 400 deg. C=> smaller=better.

SubMin400 – deviation below 400 deg.C => smaller= better.

Negative Height moves substrates down, away from base position and away from lamps.

Positive Height moves substrates up, away from base position, closer to lamp.

SubstrateMinus-Row1, Positive moves inward, negative outward

SubstratePlus-Row2, positive moves inward, negative outward

Baseline Design vs. Optimized

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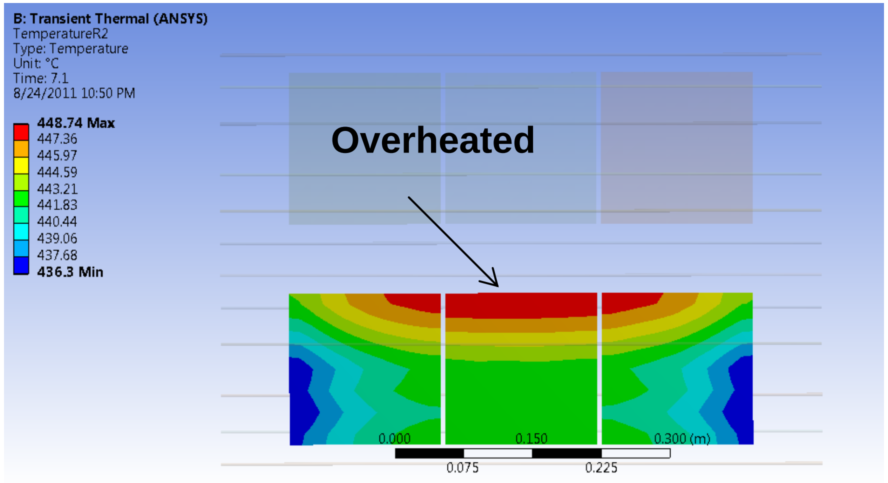
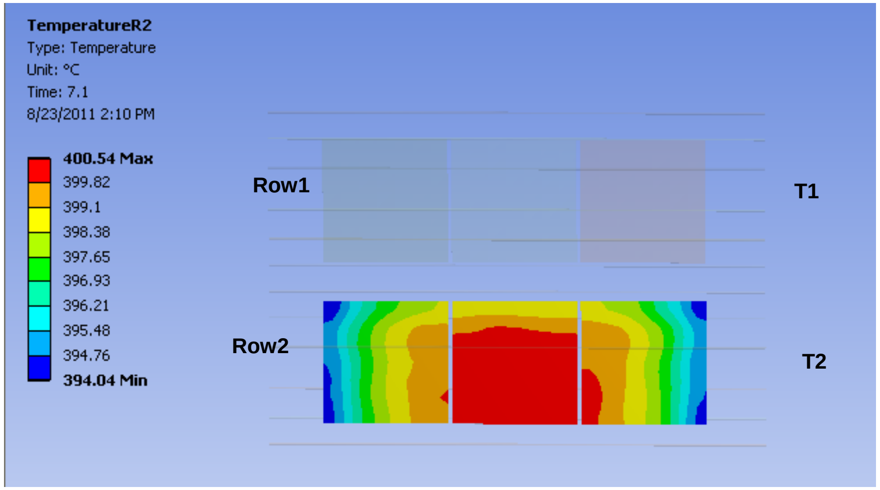
Baseline Hardware Design, all zero deviations, T1=T2=900 deg



deltaT=12.44
subMax=dev2=48.7 deg.C
(desired 10 deg or less)

One of several optimized Pareto+ designs



TempDiff ~ 6 deg. C
subMax=dev2= 0.54 deg.C

T1 dropped below T2, this way less overheating of the center zone (top edge of the substrate on the picture)

Row2 Substrates moved up (away from their more central position)

– that allows to shift temperature peak from the center zone (substrate top edge) into the middle of substrate)

Going Head-to-Head with Human

In head-to-head competitions best "human guided" (case-by-case) studies resulted in system design with ±10-20 deg.C thermal uniformity and took several weeks to accomplish, while computer optimization based approach allowed to quickly yield multiple solutions capable of reaching ± 3 deg. C. It took only two 24 hour cycles for CPU to "independently" accomplish this task.

But most importantly, multi-objective optimization analysis provided unique insights into system behavior and lead to innovative enabling design solutions. Statistical analysis of designs provided confidence that we found solutions that are truly best.

Thus, we can conclude that "Optimization Equals Innovation".

Further improvement in Design Modeler is required to allow more flexible parameterization of geometry setup, exploring ANSYS SpaceClaim can help.

Conclusion: Optimization = Innovation

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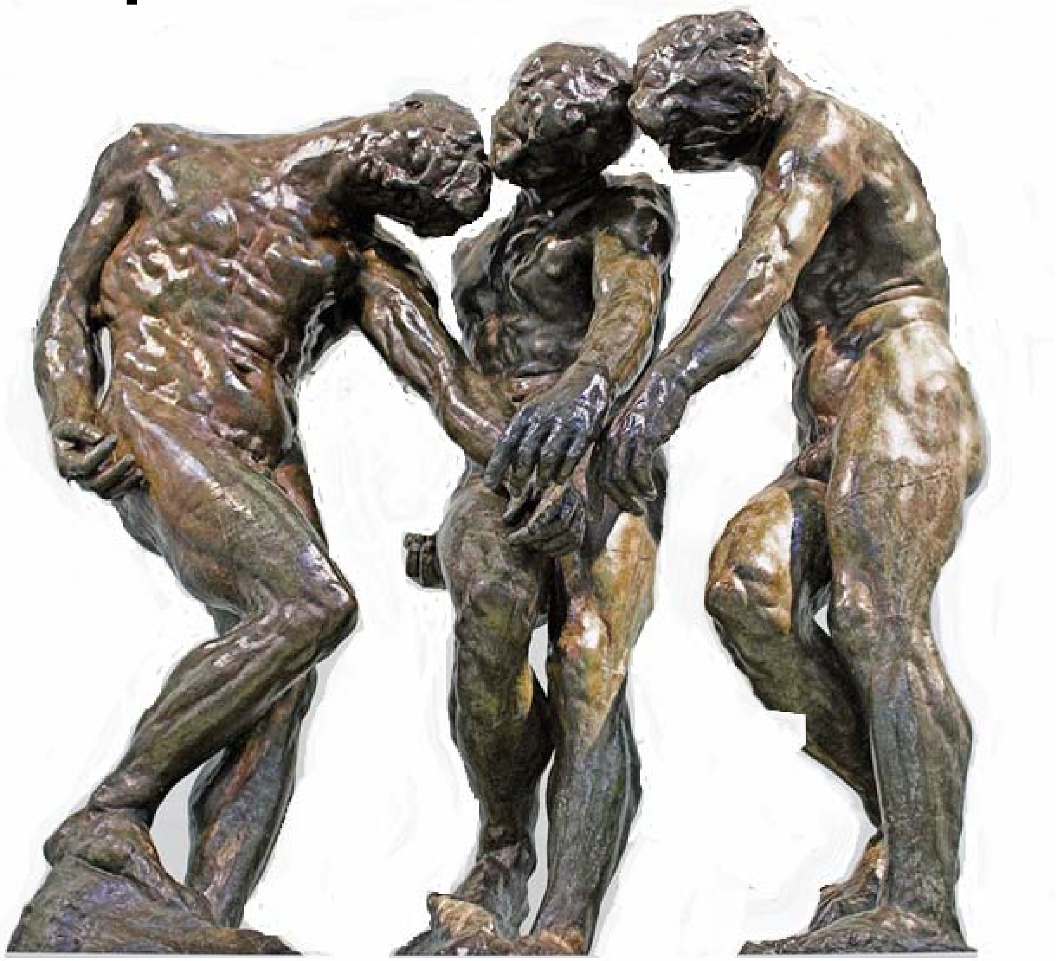

modeFrontier ANSYS eArtius

WorkBench

Acknowledgement

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