UNIVERSITY of STIRLING

Sustainable Building Design through Evolutionary Algorithms and Optimisation

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(joint work with Jon Wright et al at Loughborough University)

BE THE DIFFERENCE

Outline

Why Optimise Buildings

Exploring the design space

Challenge 1: Long Run Times

Challenge 2: Large Scale

Conclusions

Why Optimise Buildings?

Why optimise?

Climate change!

Over 50% of UK carbon emissions are related to energy consumed buildings

Cost, comfort

No mass production

Long design lifetime

Buildings are complex!

Many variables

Dimensions, materials, layout, systems (heat / light etc), control configuration

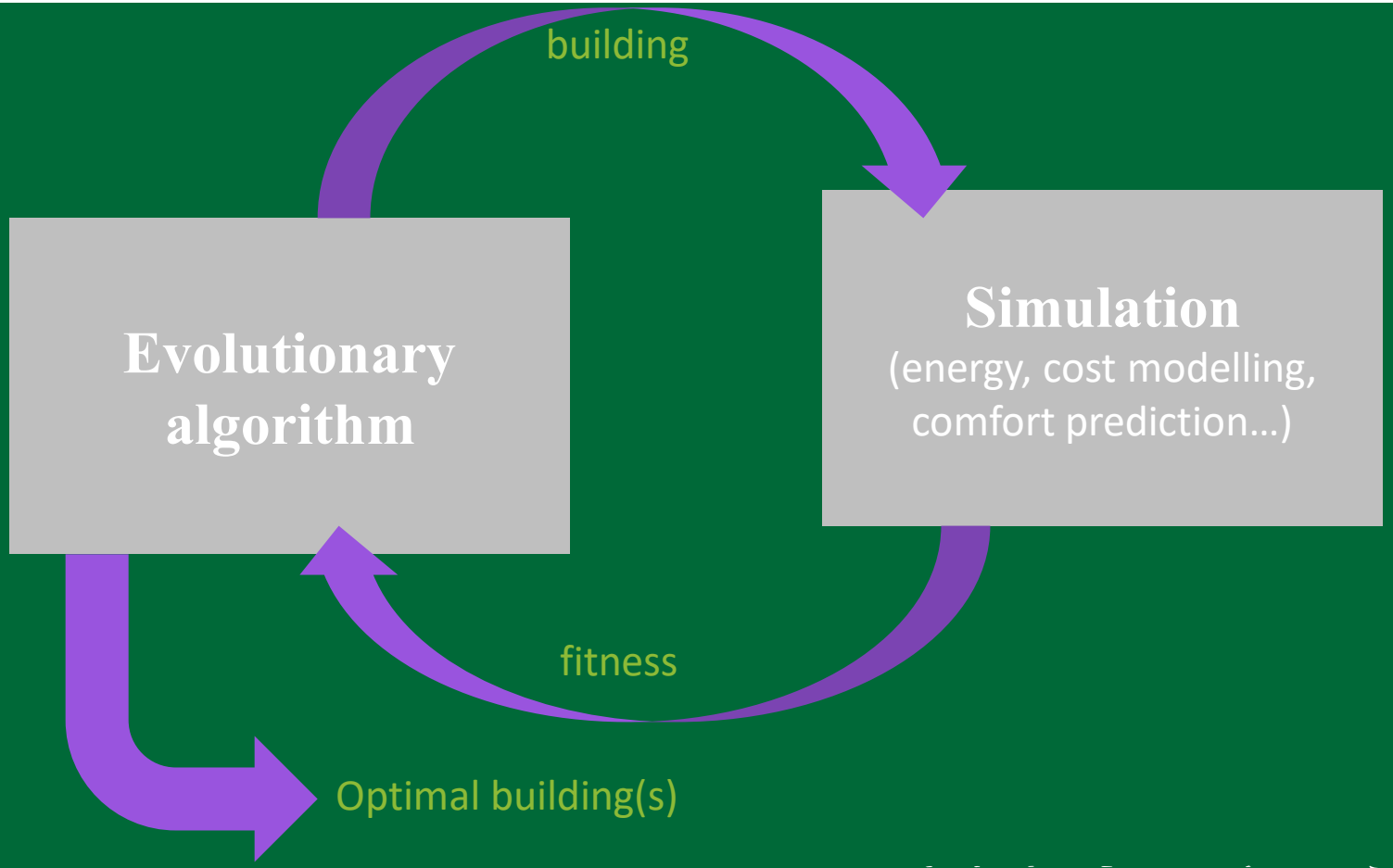
Many objectives / constraints

Energy use, Construction cost, Comfort

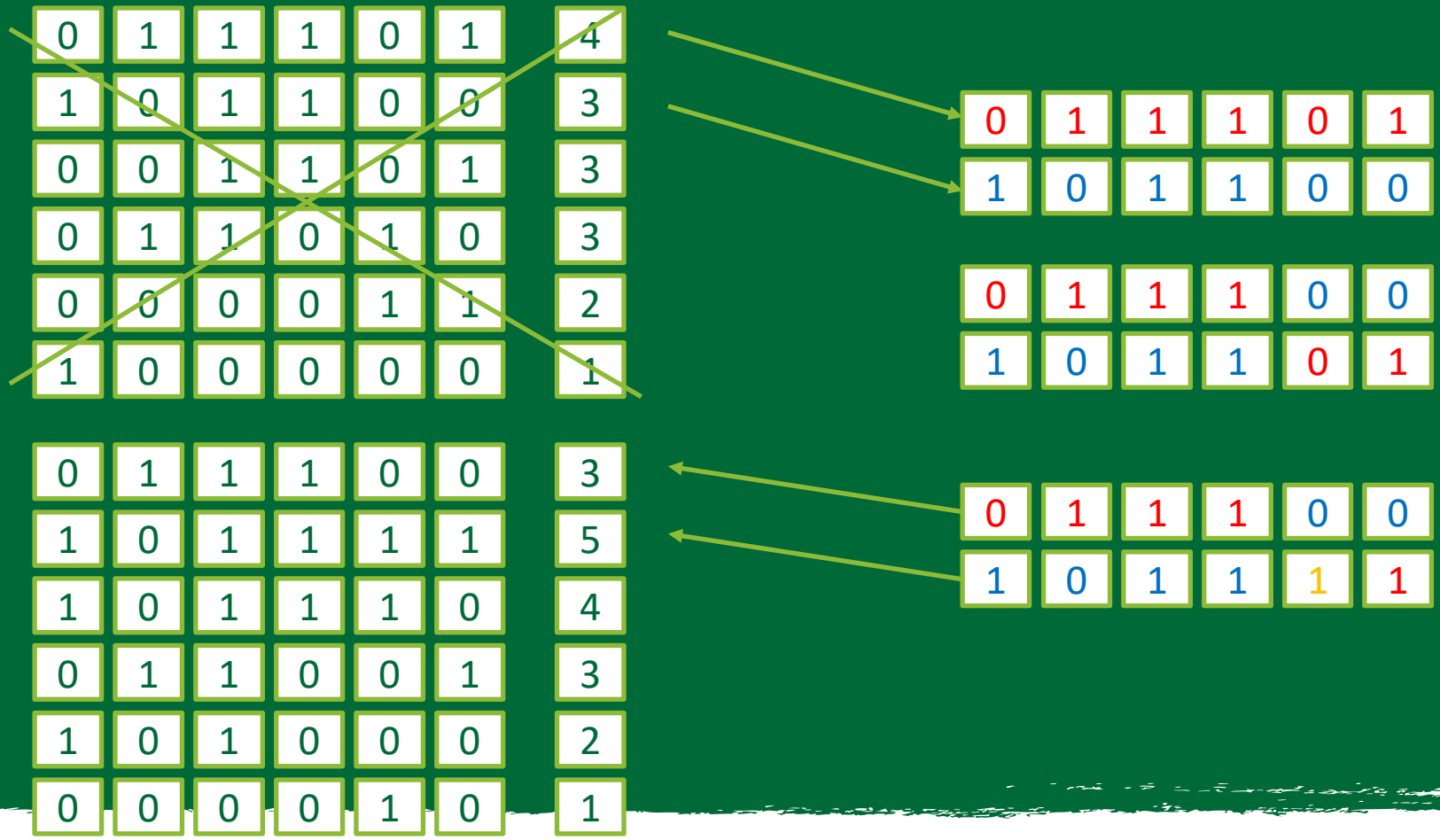
- all examples here are heat+light+cool energy vs cost (minimise both)

Comfort, Physical limitations, Compliance

Highly suitable for EA


building
Evolutionary algorithm
Simulation
(energy, cost modelling, comfort prediction…)
fitness
Optimal building(s)

Evolutionary Algorithms



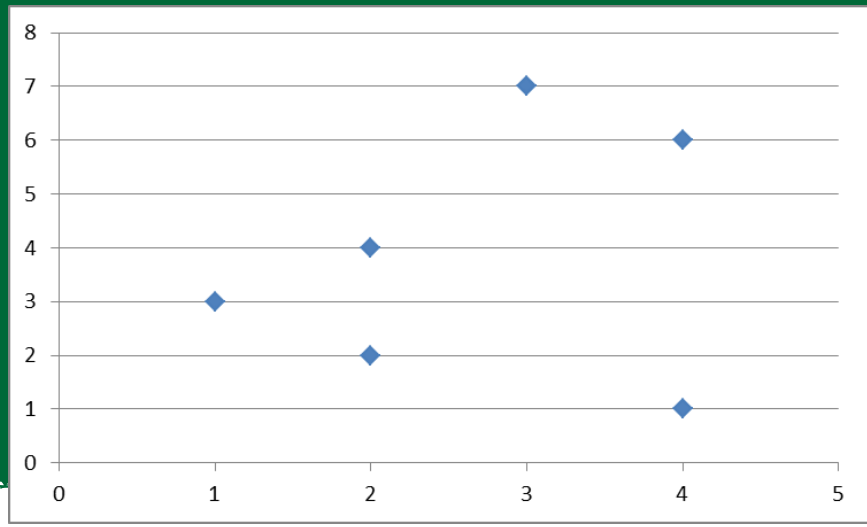
This time there are two “fitnesses” (objective values) for each solution

One solution *dominates* another if it is “better” in both objectives

Can plot the objectives of population in 2D >>>

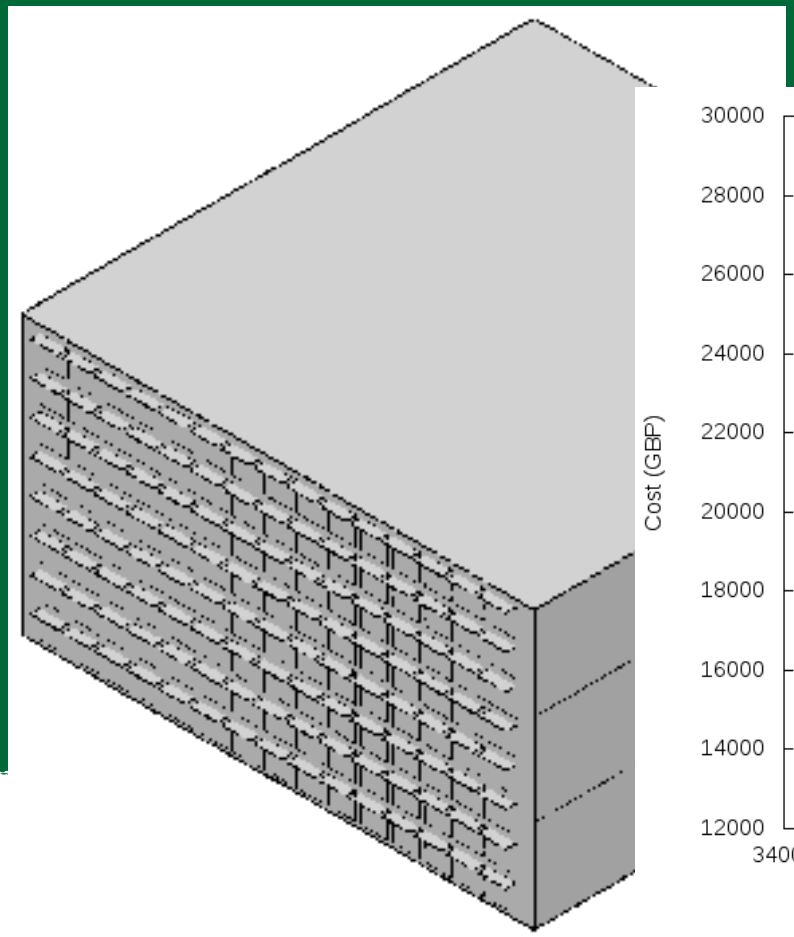
Set of non-dominated solutions is the Pareto front

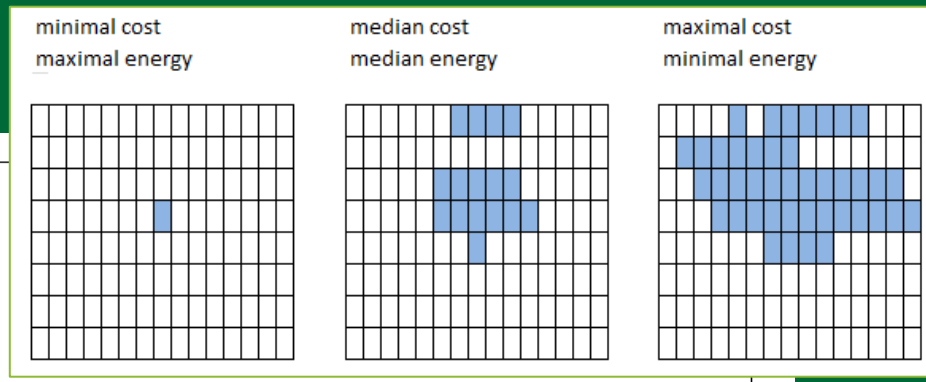
0	1	1	1	0	1	1	3
1	0	1	1	0	0	2	4
0	0	1	1	0	1	4	6
0	1	1	0	1	0	3	7
0	0	0	0	1	1	2	2
1	0	0	0	0	0	4	1



Explanation: analysis of solutions and Pareto fronts

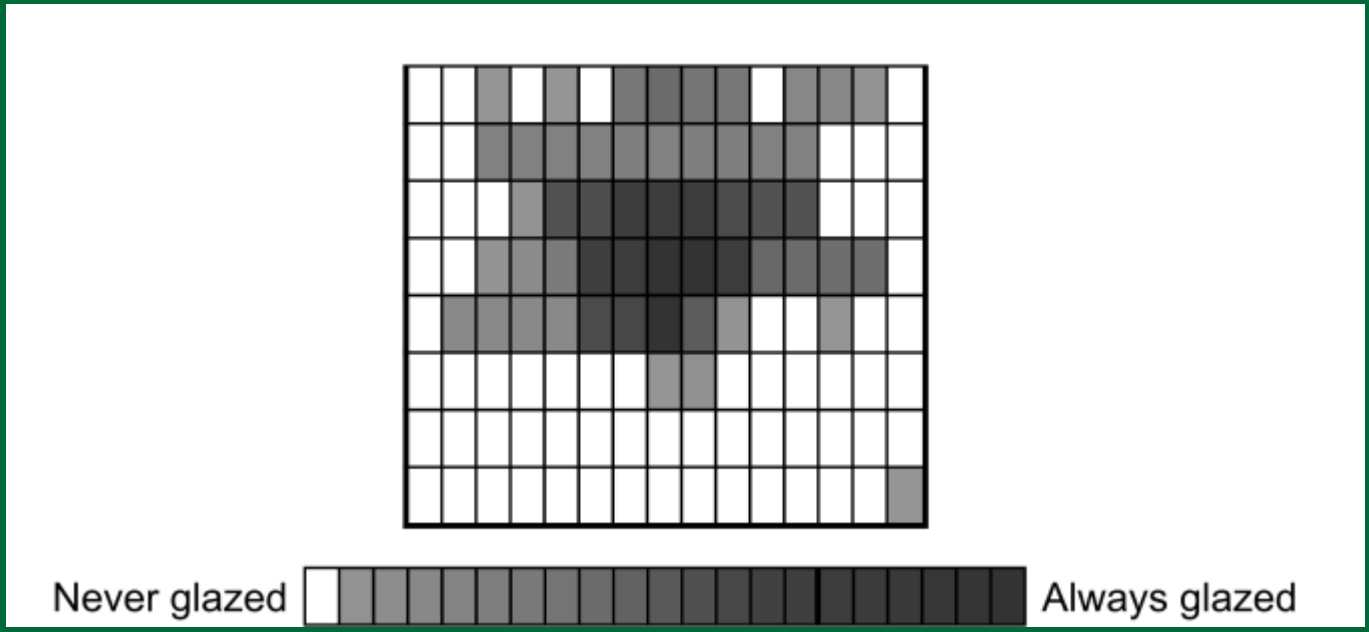
It's about informing the design process; exploration of the space





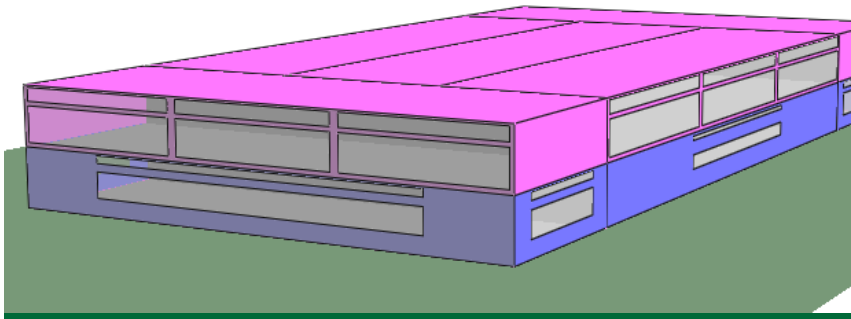
Explanation: analysis of solutions and Pareto fronts

Points common to all members of Pareto front



Expanation: analysis of solutions and Pareto fronts

Energy	CapCost	A	B	C	D	E	F	G	H	I
0.00	1.00	0.5	0.564516	0.98	0.65	0.82	0.11	0	1	1
0.01	0.90	0.5	0.564516	0.98	0.65	0.73	0.11	0	1	1
0.03	0.82	0.5	0.580645	0.98	0.57	0.73	0.11	0	1	1
0.04	0.76	0.5	0.580645	0.98	0.49	0.73	0.11	0	1	0
0.07	0.74	0.5	0.564516	0.98	0.49	0.73	0.11	0	1	0
0.07	0.70	0.5	0.564516	0.98	0.49	0.73	0.22	0	1	0
0.10	0.66	0.5	0.580645	0.98	0.41	0.73	0.11	0	1	0
0.10	0.62	0.5	0.564516	0.98	0.65	0.82	1.00	1	1	1
0.10	0.61	0.5	0.564516	0.98	0.65	0.82	0.11	1	1	1
0.10	0.61	0.5	0.564516	0.98	0.65	0.82	1.00	1	1	1
0.12	0.59	0.5	0.612903	0.98	0.65	0.82	0.67	1	1	1
0.14	0.57	0.5	0.548387	0.98	0.49	0.73	0.11	1	1	0
0.15	0.54	0.4	0.548387	0.98	0.57	0.73	0.67	1	1	0
0.17	0.53	0.4	0.548387	0.98	0.57	0.73	0.67	1	1	0
0.18	0.52	0.5	0.564516	0.98	0.49	0.73	0.11	1	1	0
0.18	0.49	0.4	0.548387	0.98	0.57	0.73	0.67	1	1	0
0.21	0.45	0.4	0.564516	0.98	0.41	0.43	0.11	0.5	1	0
0.21	0.43	0.5	0.564516	0.98	0.57	0.43	0.67	1	1	0
0.21	0.37	0.4	0.548387	0.98	0.49	0.43	0.67	1	1	0
0.24	0.35	0.4	0.548387	0.98	0.49	0.43	0.67	1	1	0
0.27	0.32	0.4	0.548387	0.98	0.41	0.43	0.11	1	1	0
0.32	0.30	0.4	0.548387	0.98	0.33	0.43	0.67	1	1	0
0.33	0.29	0.4	0.548387	0.98	0.33	0.43	0.11	1	1	0
0.35	0.27	0.4	0.580645	0.98	0.35	0.43	0.11	1	1	0
0.35	0.26	0.4	0.596774	0.98	0.24	0.43	0.11	1	1	0
0.36	0.25	0.4	0.548387	0.98	0.29	0.43	0.11	1	1	0
0.38	0.25	0.4	0.596774	0.98	0.33	0.33	0.11	1	1	0
0.39	0.25	0.4	0.596774	0.98	0.33	0.33	0.11	1	1	0
0.39	0.24	0.4	0.596774	0.98	0.33	0.33	0.11	1	1	0
0.41	0.20	0.4	0.596774	0.98	0.33	0.33	0.67	1	1	0
0.46	0.20	0.4	0.596774	0.98	0.33	0.33	0.11	1	1	0
0.46	0.20	0.4	0.596774	0.98	0.33	0.33	0.11	1	1	0
0.47	0.19	0.4	0.564516	0.98	0.24	0.33	0.11	1	1	0
0.49	0.18	0.4	0.596774	0.98	0.24	0.33	1.00	1	1	0
0.54	0.16	0.4	0.532258	1.00	0.24	0.33	0.11	1	1	0
0.55	0.14	0.4	0.596774	0.98	0.24	0.33	0.67	1	1	0
0.57	0.12	0.4	0.596774	0.98	0.24	0.33	0.11	1	1	0
0.64	0.11	0.4	0.612903	0.98	0.24	0.43	0.11	1	1	0



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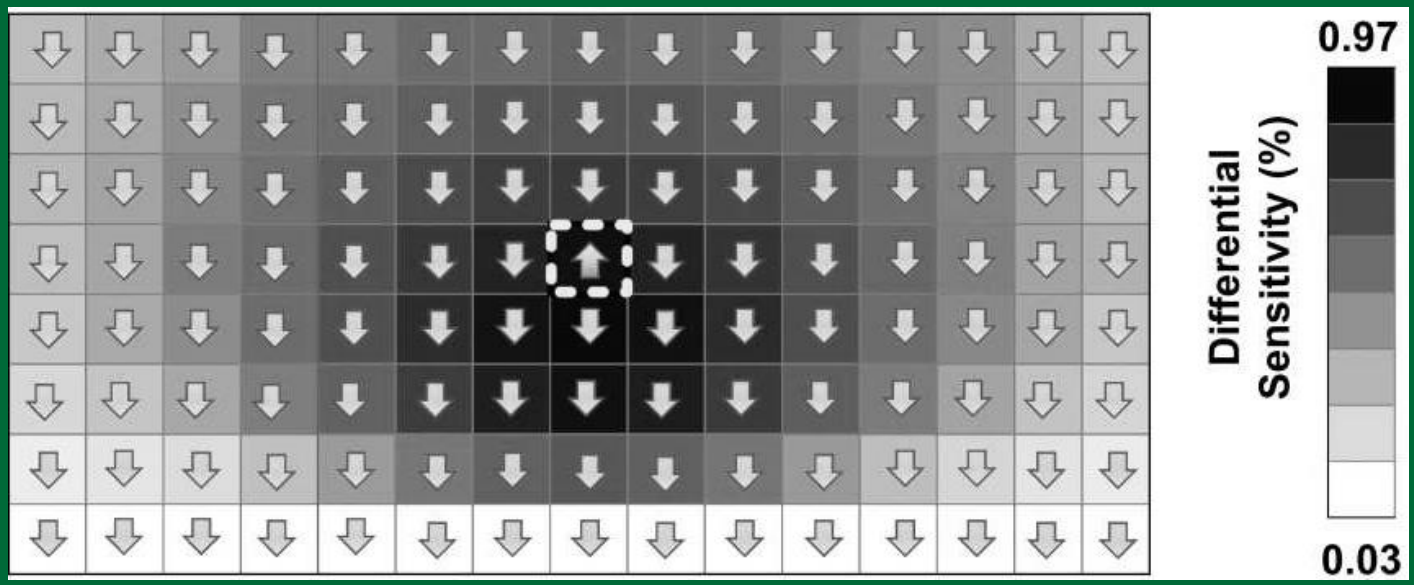
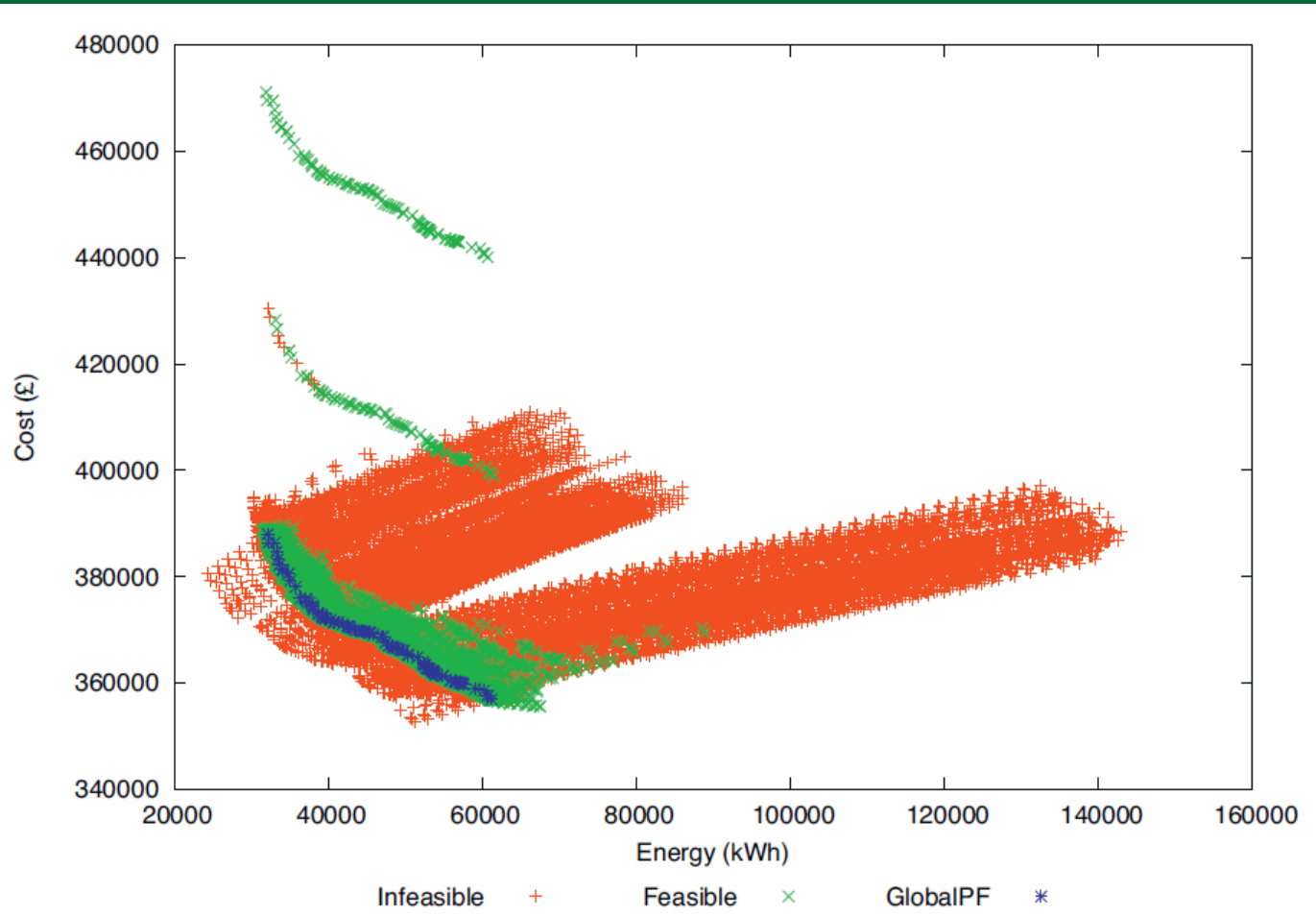
Local sensitivity

Local sensitivity

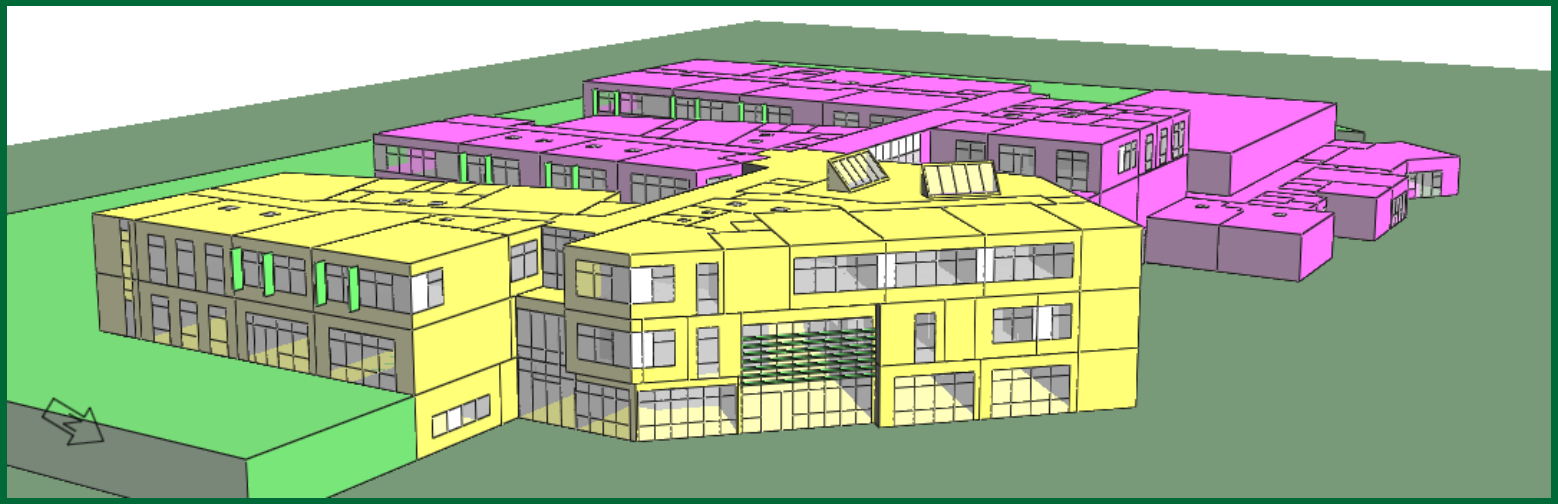


Local sensitivity

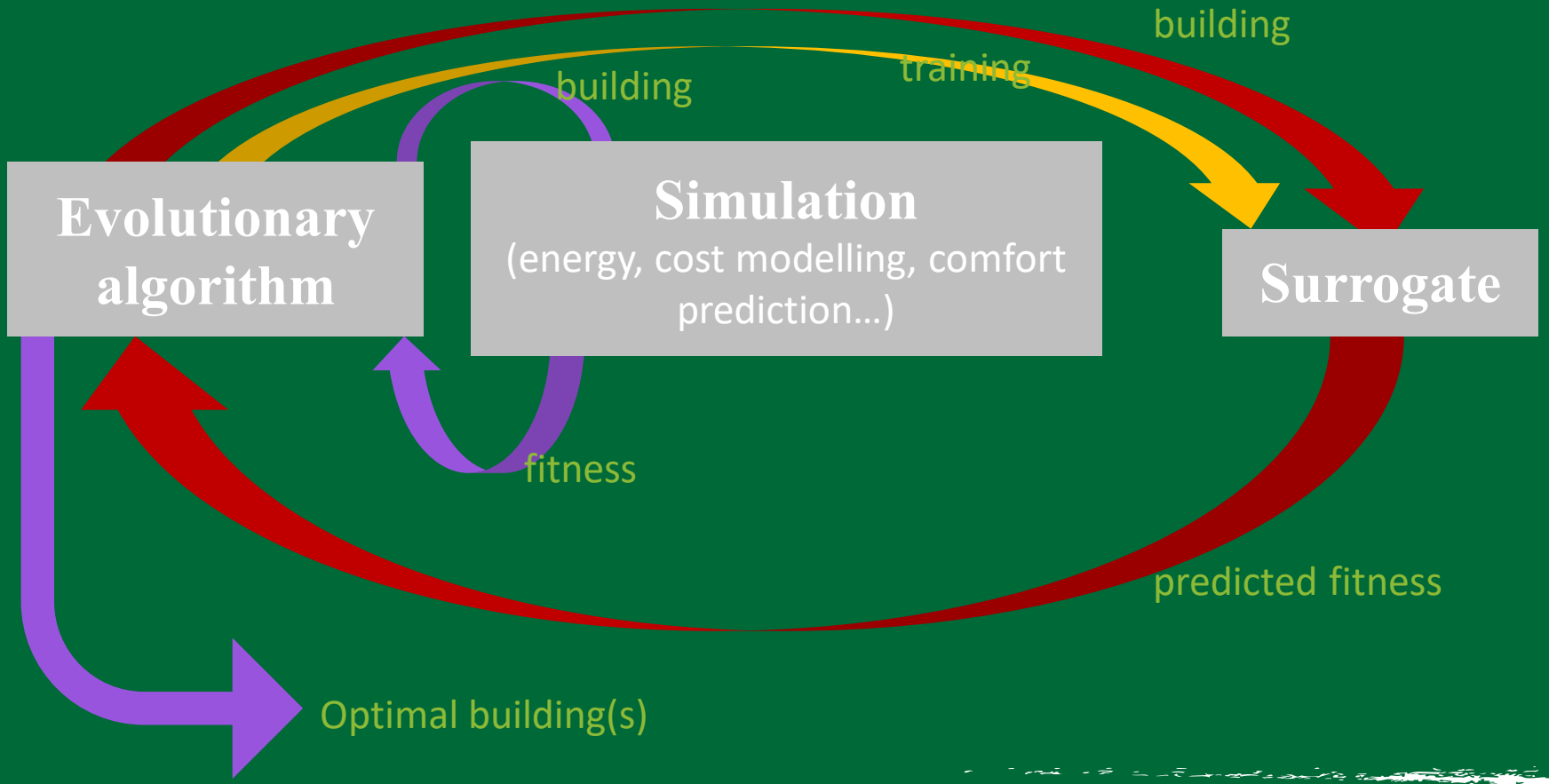


Challenge 1: Long Run Times

Evaluations at least 1-2 minutes, up to hours



Challenge 1: Long Run Times



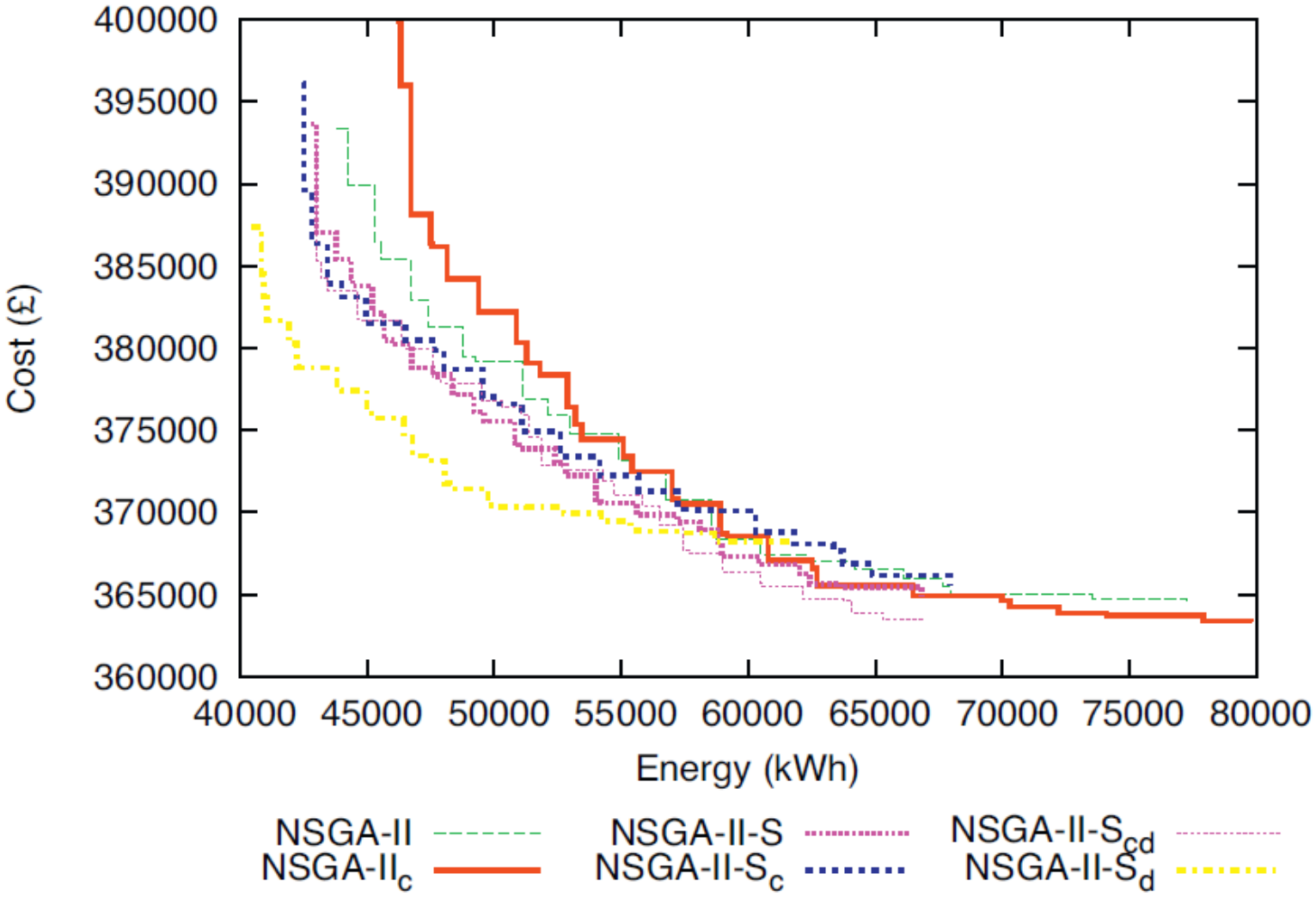
Surrogate models

Approximate the fitness function

Don’t always get it right!

Separate models for each objective and constraint

Always keep some “predicted infeasible” solutions in population


400000
395000
390000
385000
380000
375000
370000
365000
360000
Cost (£)
40000
45000
50000
55000
60000
65000
70000
75000
80000
Energy (kWh)
NSGA-II
NSGA-II$_c$
NSGA-II-S
NSGA-II-S$_c$
NSGA-II-S$_{cd}$
NSGA-II-S$_d$

Challenge 2: Large Scale

- 935 houses in NE England (actually representative *archetypes* representing 1.2 million homes)
- 4424 binary decisions about whether to apply or not apply a refurbishment
- (approx. 4.73 decisions per house)
- Data taken from Cambridge Housing Model (in turn built on data from the English Housing Survey)

Refurbishment	Cost (£)
Cavity wall insulation (CWI)	500
Loft insulation (Loft)	250
Double glazing (DG)	5000
Condensing boiler (Cond)	2500
Solid wall insulation (SWI)	8000
Air source heat-pump (ASHP)	7000
Ground source heat-pump (GSHP)	10000
Biomass heat (BH)	10000
Photovoltaic cells (PV)	8000
Solar hot water (SHW)	2000

Global optimisation problem

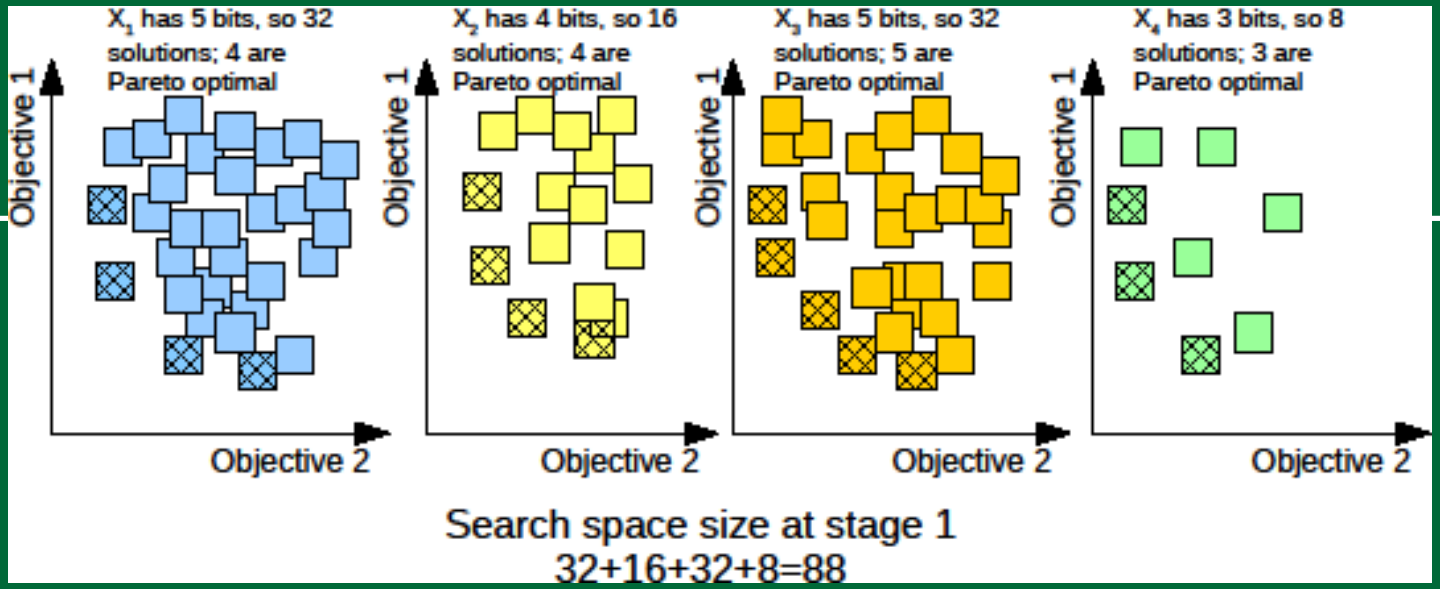
How do we best invest our limited budget across the whole stock?

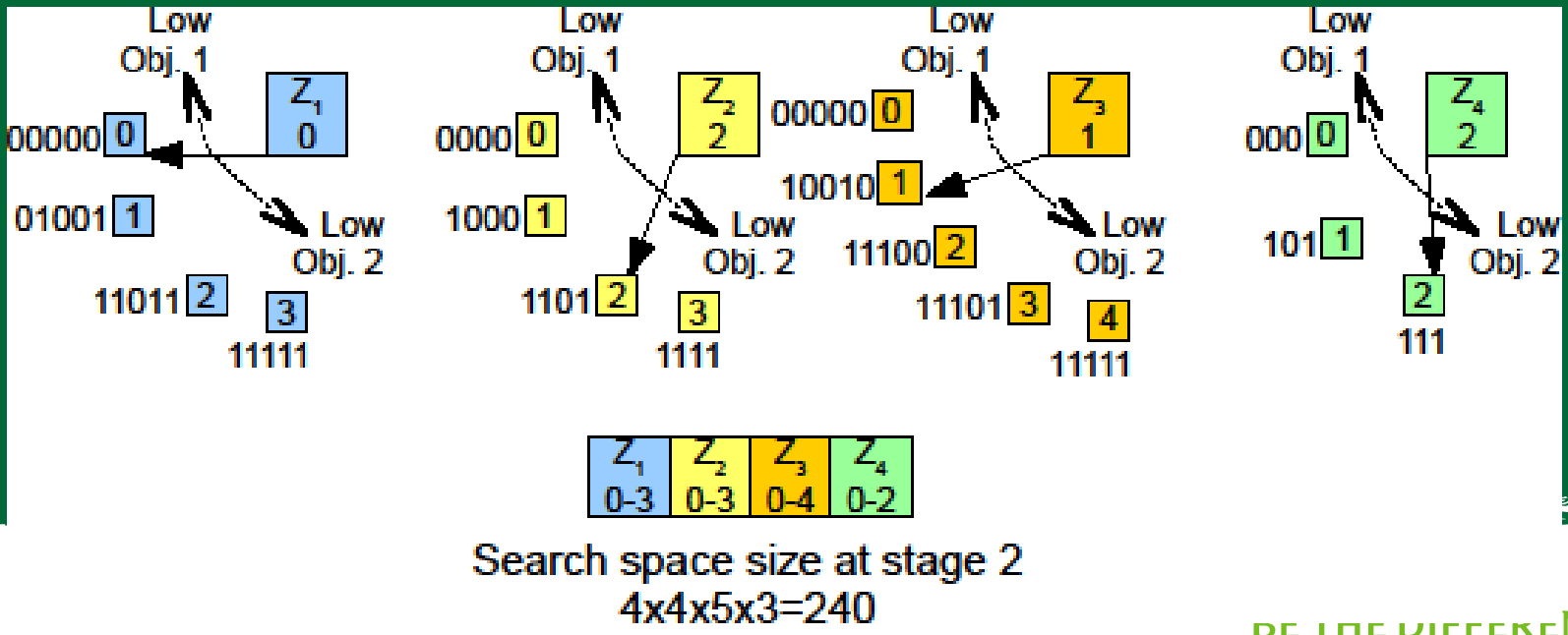
The single-objective version of problem (minimise cost, or minimise energy) is *additively-separable*

Multi-objective version isn't separable

$$F(X) = \sum_{I=1}^{S} G(X_I)$$

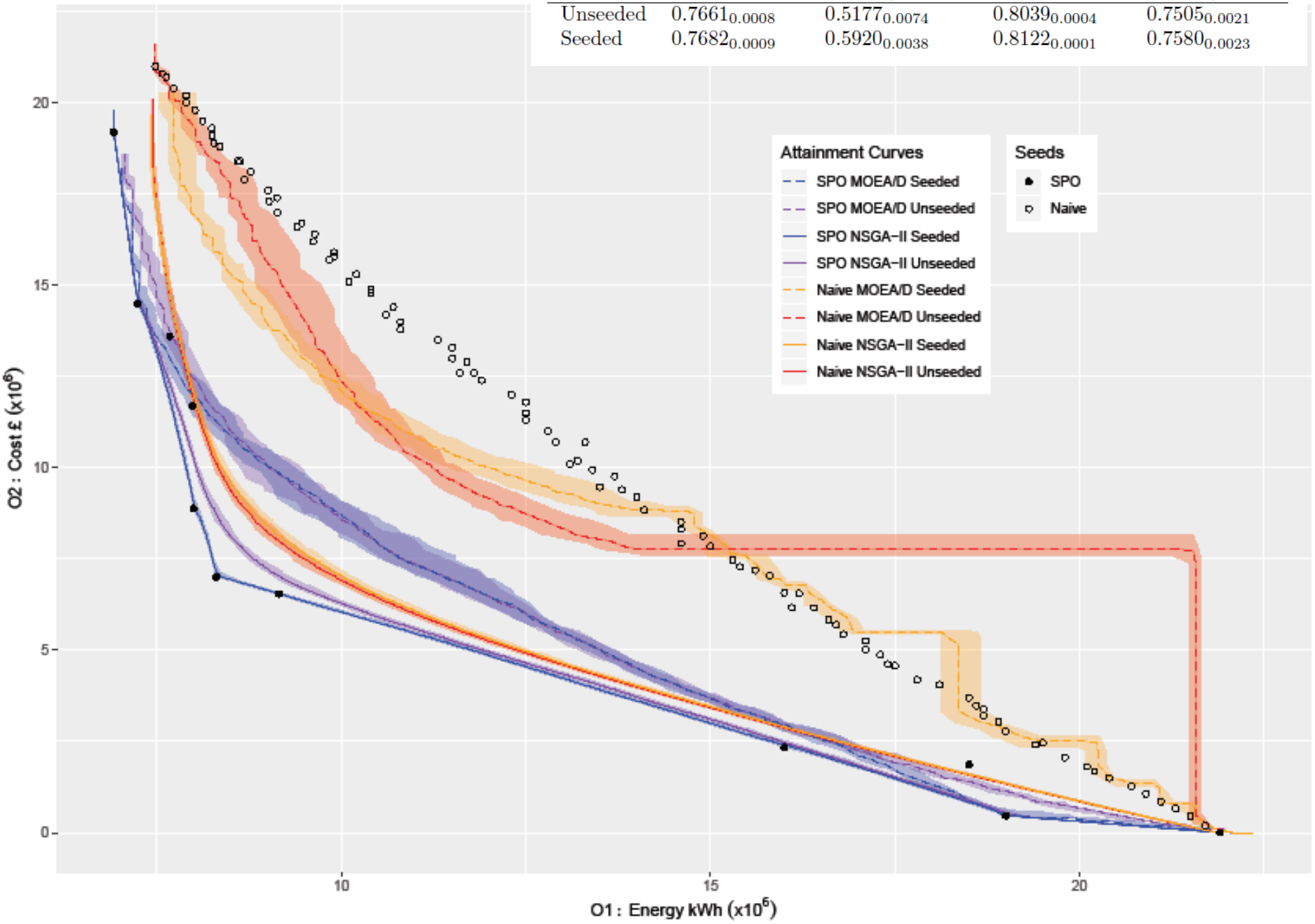
Sub-problem $G(X_1)$					$G(X_2)$				$G(X_3)$					$G(X_4)$		
X_{1_1} 0-1	X_{1_2} 0-1	X_{1_3} 0-1	X_{1_4} 0-1	X_{1_5} 0-1	X_{2_1} 0-1	X_{2_2} 0-1	X_{2_3} 0-1	X_{2_4} 0-1	X_{3_1} 0-1	X_{3_2} 0-1	X_{3_3} 0-1	X_{3_4} 0-1	X_{3_5} 0-1	X_{4_1} 0-1	X_{4_2} 0-1	X_{4_3} 0-1
$2^5=32$					$2^4=16$				$2^5=32$					$2^3=8$		

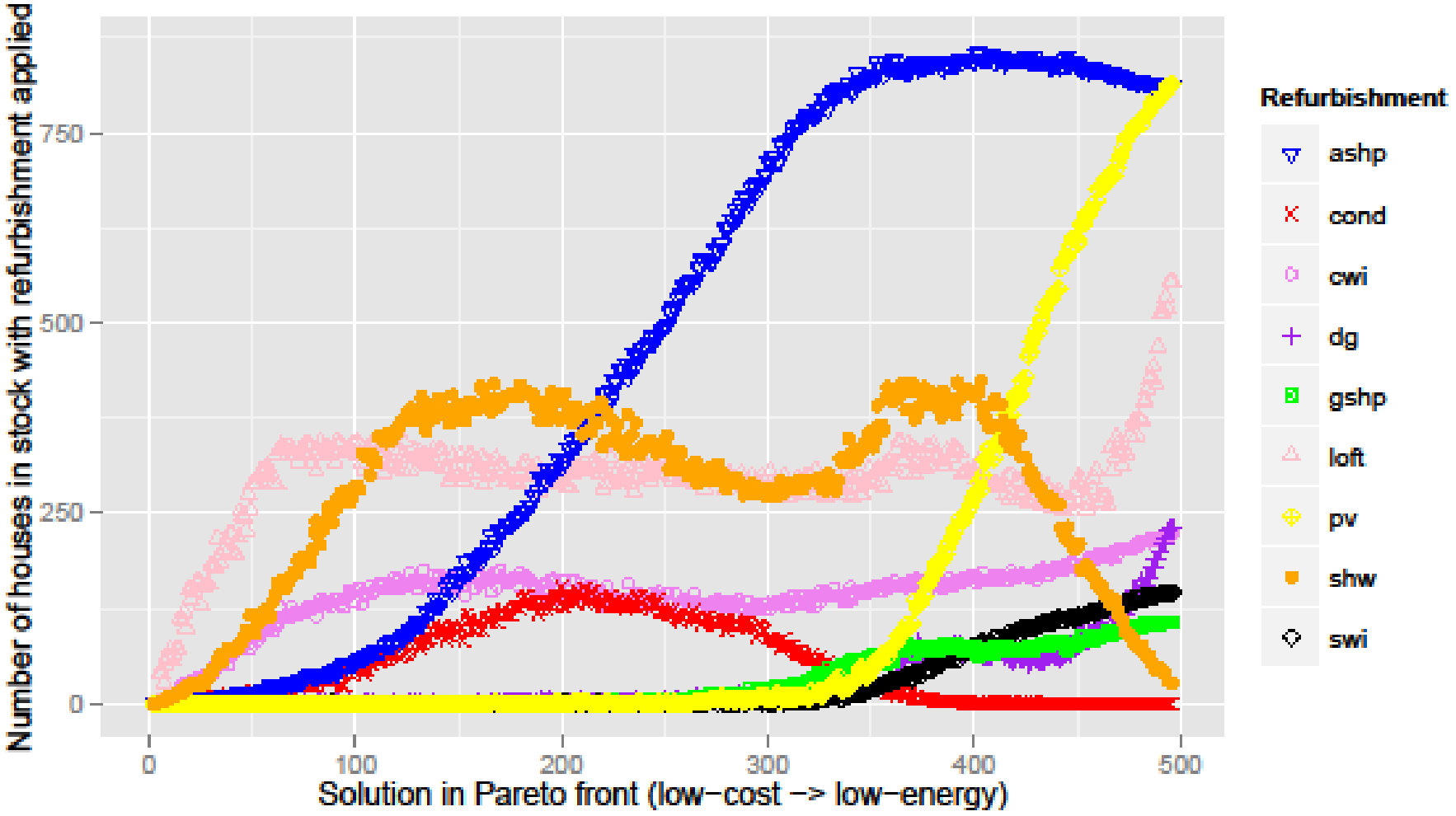

X1 has 5 bits, so 32 solutions; 4 are Pareto optimal
X2 has 4 bits, so 16 solutions; 4 are Pareto optimal
X3 has 5 bits, so 32 solutions; 5 are Pareto optimal
X4 has 3 bits, so 8 solutions; 3 are Pareto optimal
Objective 1
Objective 2
Search space size at stage 1
32+16+32+8=88


Low Obj. 1
Low Obj. 2
Z1
Z2
Z3
Z4
00000 0
01001 1
11011 2
11111 3
0000 0
1000 1
1101 2
1111 3
00000 0
10010 1
11100 2
11101 3
11111 4
000 0
101 1
111 2
Z1 0-3
Z2 0-3
Z3 0-4
Z4 0-2
Search space size at stage 2
4x4x5x3=240

Results

	Naive NSGA-II	Naive MOEA/D	SPO NSGA-II	SPO MOEA/D
Unseeded	$0.7661_{0.0008}$	$0.5177_{0.0074}$	$0.8039_{0.0004}$	$0.7505_{0.0021}$
Seeded	$0.7682_{0.0009}$	$0.5920_{0.0038}$	$0.8122_{0.0001}$	$0.7580_{0.0023}$




Number of houses in stock with refurbishment applied
0
250
500
750
0
100
200
300
400
500
Solution in Pareto front (low−cost −> low−energy)
Refurbishment
ashp
cond
cwi
dg
gshp
loft
pv
shw
swi

Summary

Building optimisation is important!

Exploration of the design space is as important as finding (near) optimal solutions

Surrogates used to speed up runs

Reformulation of the problem to solve at large scale

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