Multi-objective optimisation of building designs

Sandy Brownlee

Research Associate, Loughborough University

Outline

- Me
- Evolutionary Multi-objective Optimisation
- Building design optimisation
- Improvements
  - Constraints
  - Surrogates
  - Inheritance
- Conclusions, questions etc.

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Me

- Former RGU PhD, now RA at Loughborough
- TSB / EPSRC funded project – this talk
  - *A Simulation-based Optimisation Tool for the Minimisation of Building Carbon Emission and Water Usage*
  - Civil & Building @ lboro + consortium of industrial partners
- Other interests…
  - Fitness modelling in EA
  - Deepening understanding of EA & problems
  - Applications

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Evolutionary Multi-Objective Optimisation

EMO

- Single objective GA
- Moving to multi-objective
- Constraints
- Performance indicators
- NSGA-II

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Single objective GA

1. Generate random population
2. Assign a *fitness* to members of the population
3. Choose the best ones and recombine them to produce *offspring*
4. Mutate the offspring
5. Repeat 1-4 until we're done

SO GA Example

0	1	1	1	0	1	4
1	0	1	1	0	0	3
0	0	1	1	0	1	3
0	1	1	0	1	0	3
0	0	0	0	1	1	2
1	0	0	0	0	0	1

0	1	1	1	0	1
1	0	1	1	0	0

0	1	1	1	0	0
1	0	1	1	0	1

0	1	1	1	0	0
1	0	1	1	1	1

0	1	1	1	0	0	3
1	0	1	1	1	1	5
1	0	1	1	1	0	4
0	1	1	0	0	1	3
1	0	1	0	0	0	2
0	0	0	0	1	0	1

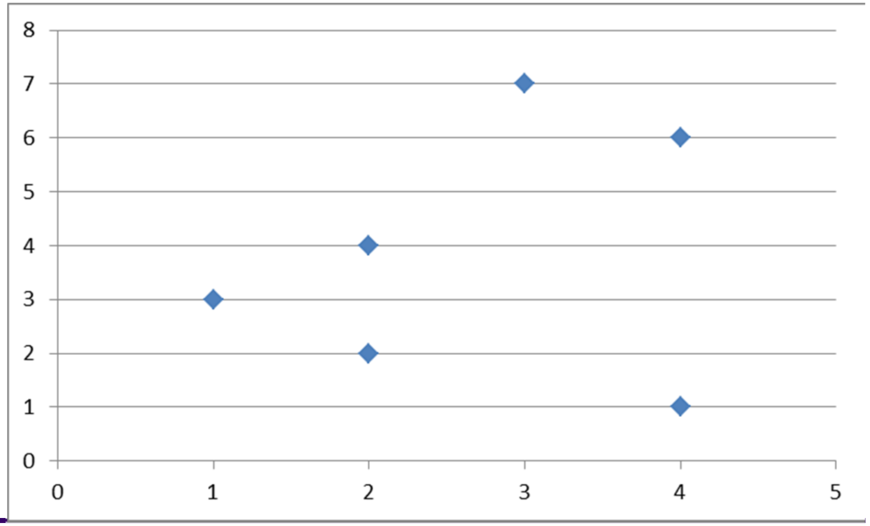
Multi-objective

- Multi-objective optimisation…
- In reality, most problems are multi-objective, often with conflicts – e.g. cost vs performance
- How do we define fitness for more than one objective?
- Could just add them together, but how do we weight them?
- Better to find the trade-off an make an informed decision

Dominance

- 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

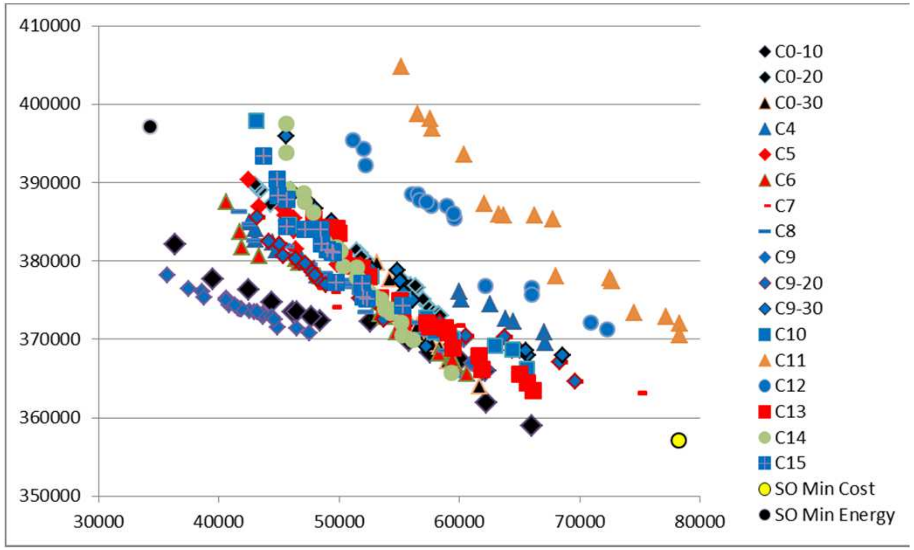


Constraints

- Some solutions might be fit, but are otherwise unwanted
  - Building with no ventilation is cheap and low-energy, but not very comfortable!
  - Examples: max hours over 28^{o}C, min lighting, compliance with building regs
- Penalty functions, algorithm enhancements
  - Whole area of research in itself
  - Can be included in the concept of dominance
- Constraints can be hard to satisfy

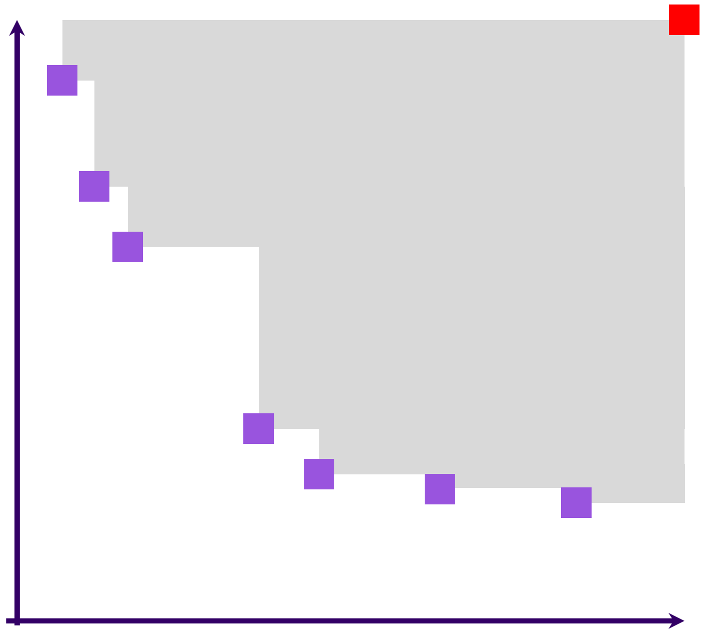
Comparing performance

- Hard to compare fronts
- What are we measuring?
  - Closeness to “true” Pareto front
  - Spread along the front
  - Extents of front
- Several measures; hypervolume used here



Hypervolume

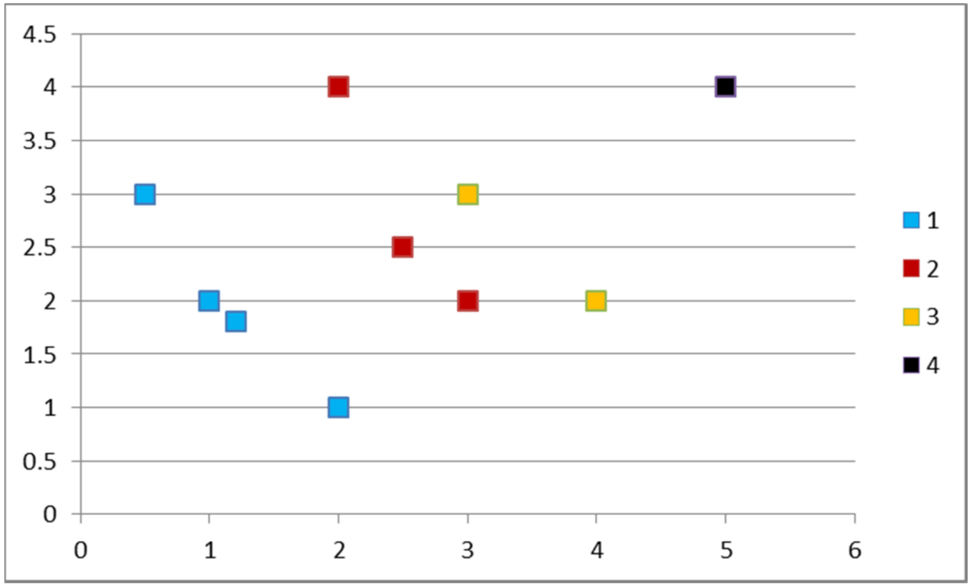
- The area / volume between the PF and a nadir point (the global minimum)
- General measure; includes extent, spread and optimality of PF
- Prefers convex regions of PF
- Expensive if many objectives



NSGA-II

- A popular GA for MO optimisation
- Selection biases search towards:
  - Feasible solutions
  - Non-dominated solutions (low rank)
  - Non-crowded solutions
- Basis for the experiments here

Non-dominated sorting / ranking



Building design optimisation

Building Designs

- Broad concepts
- 3 example problems, with results
- Variable sensitivity

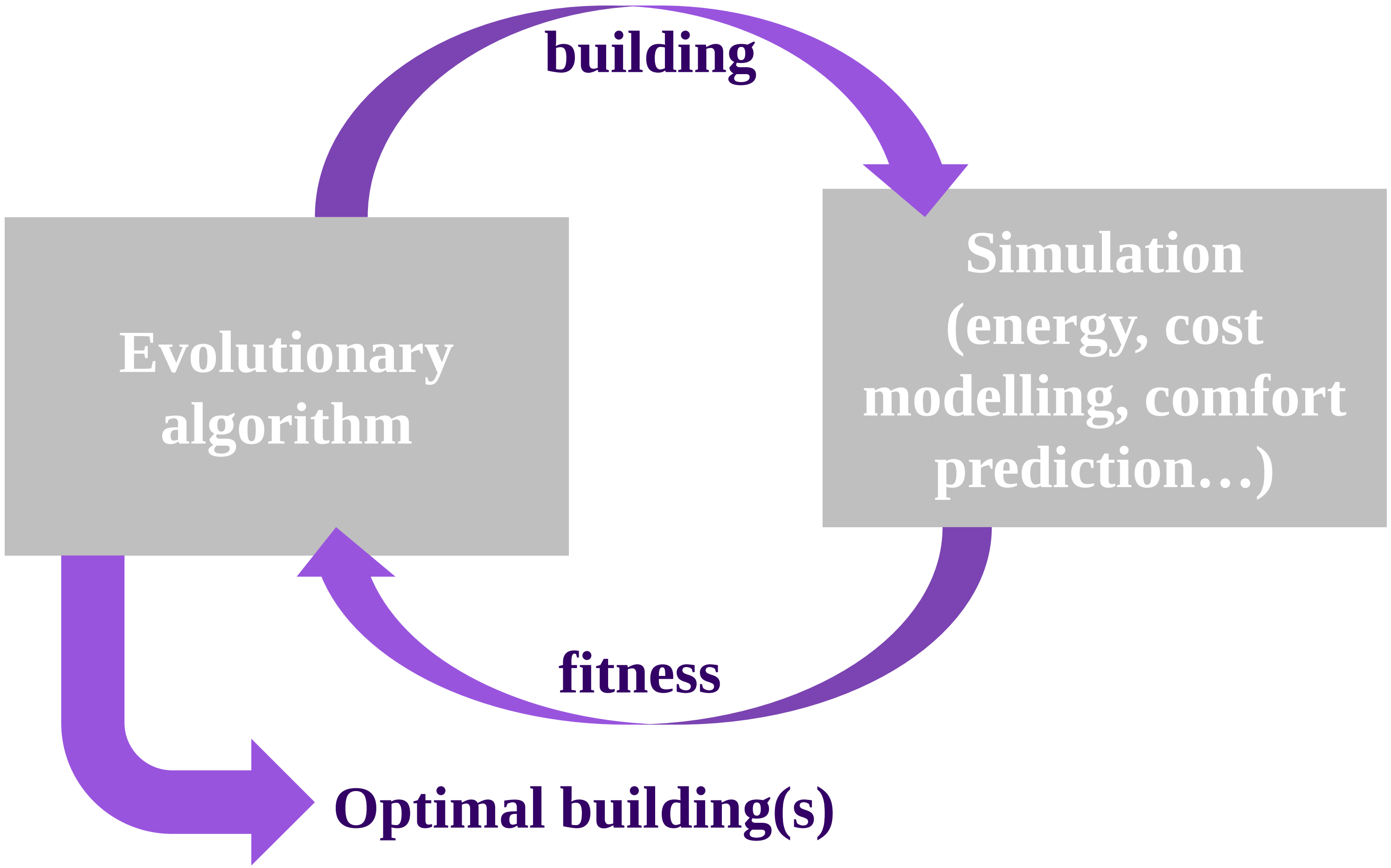
Building design optimisation

- Buildings are complex!
- Many variables
  - Dimensions, materials, layout, systems (heat / light etc), control configuration
- Many objectives / constraints
  - Energy use, Construction cost, Comfort
  - Compliance
- Highly suitable for EA

Building design optimisation

- Different design stages
  - Conceptual
  - Scheme
  - Detailed
- Change at concept stage can be big
  - But also dependent on getting things right later
- Project blurring lines between stages; optimise across stages (e.g. orientation, envelope, controls) but more to be done

Building design optimisation



Example 1: Cellular Windows

- Optimise glazing for an atrium in a building
- Switch on glazing and shades in 120 cells
  - 240 bits encoding
- Minimise energy use, or energy and cost
  - Energy for lighting, heating and cooling
- Constraints: number or aspect ratio of "windows" (mutually neighbouring cells)

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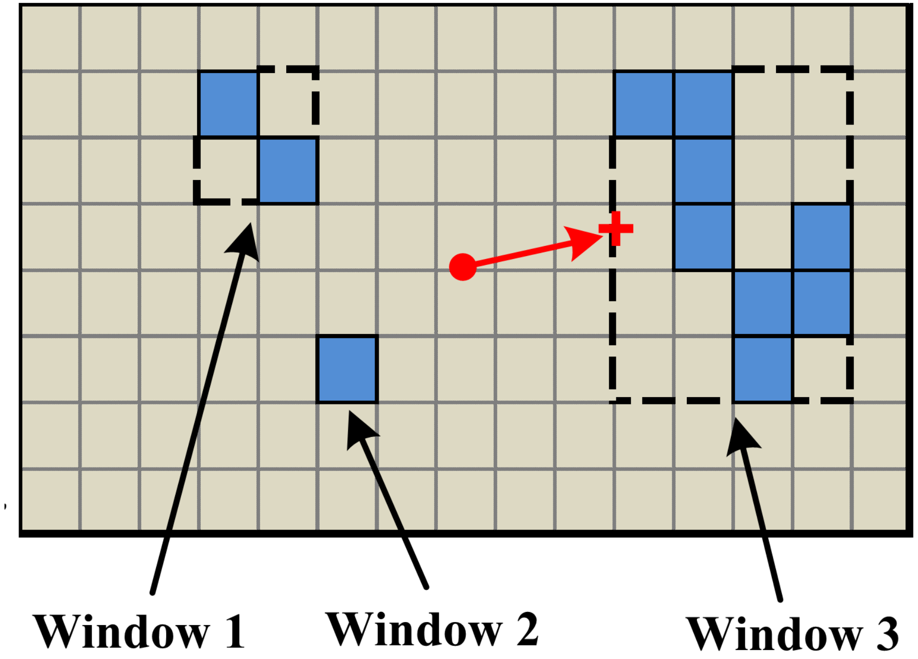
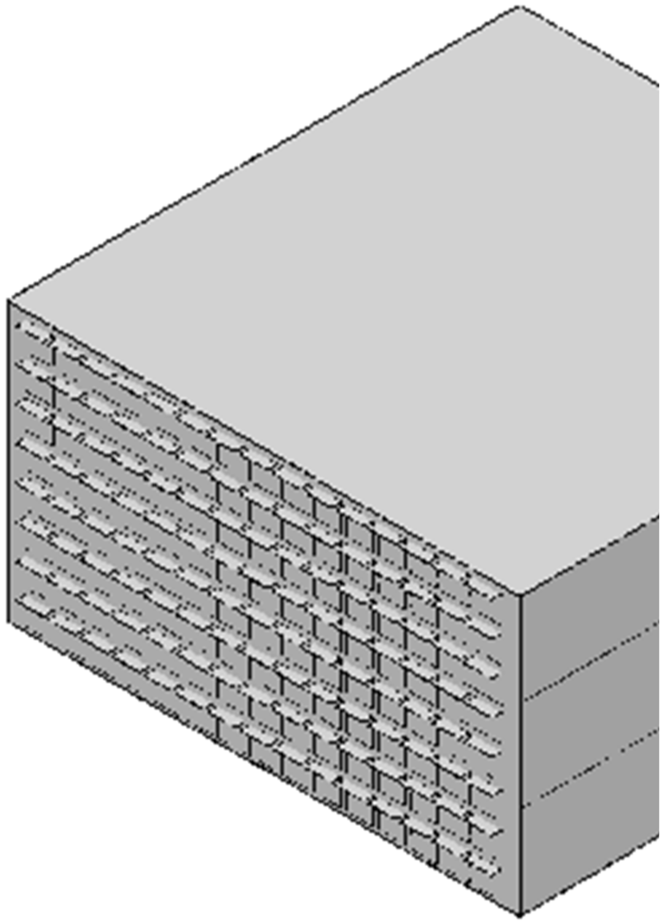
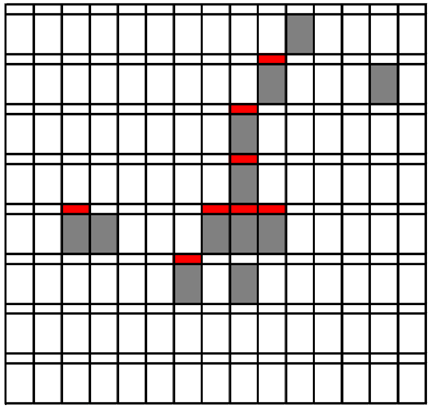
Example 1: Cellular Windows

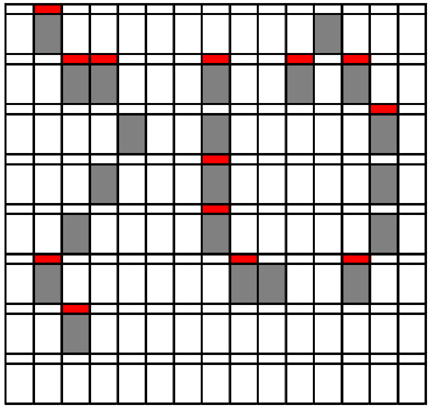




Single Objective

- With “number” constraint, glazing falls in central area
  - Where the light sensors are located
- With aspect ratio constraint, glazing tends to be spread out, still usually 3 windows
  - Better coverage of facade





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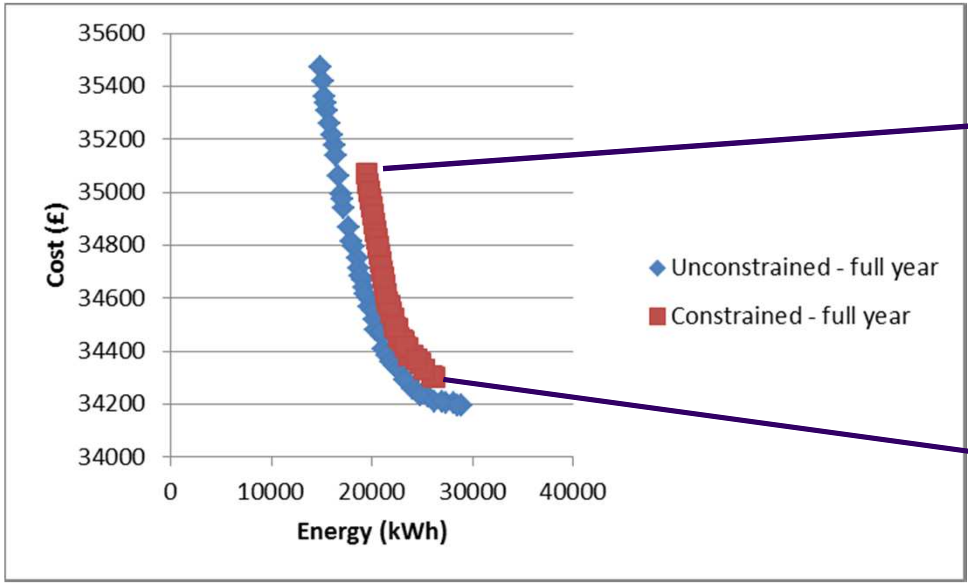
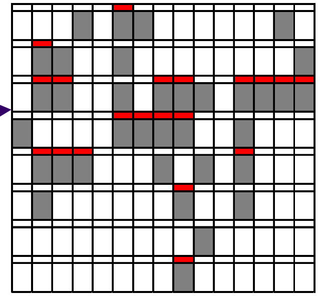
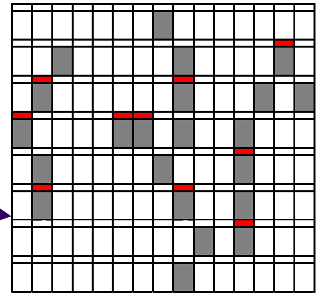
Multi-objective



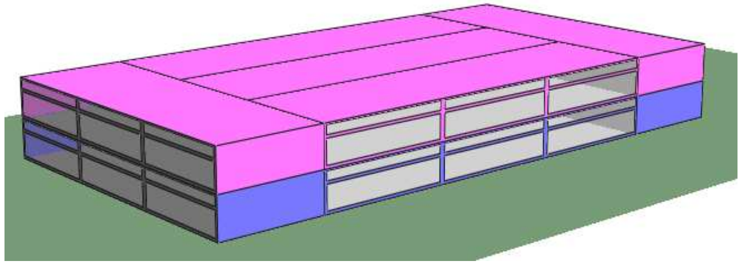




- Trade-off for energy vs cost
  - Simple linear cost per glazed cells & shades
- Larger window still tends to centre
- Hard to meet constraints
- Seeding the population helps

Example 2: Office block

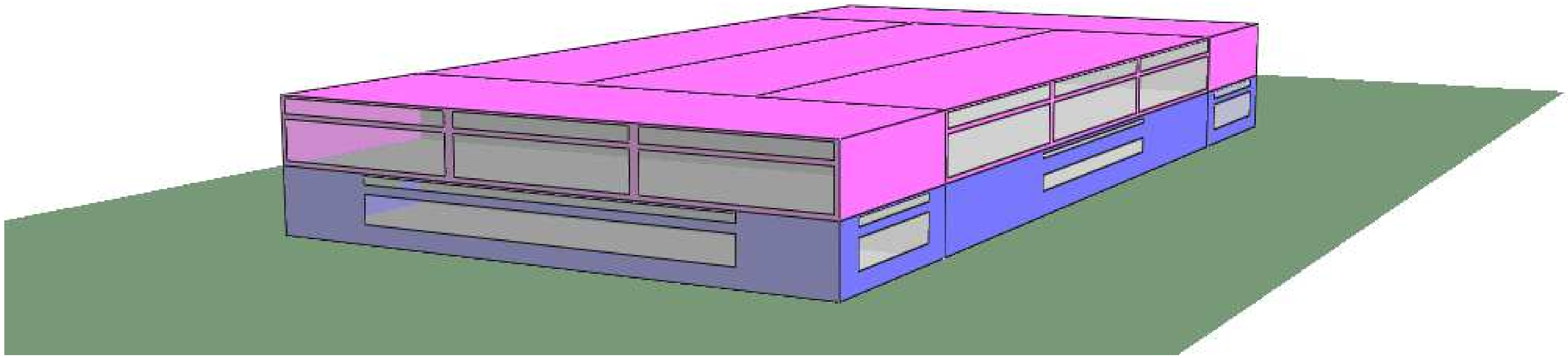
- Small 5 zone office; a single floor of a larger building
- Variables
  - Orientation, glazing area, type, wall/floor types, HVAC set points and times
- Objectives
  - Energy use, cap cost



- Constraints
  - Thermal comfort, air quality (CO_2 levels)

Results

- Example building with glazing altered



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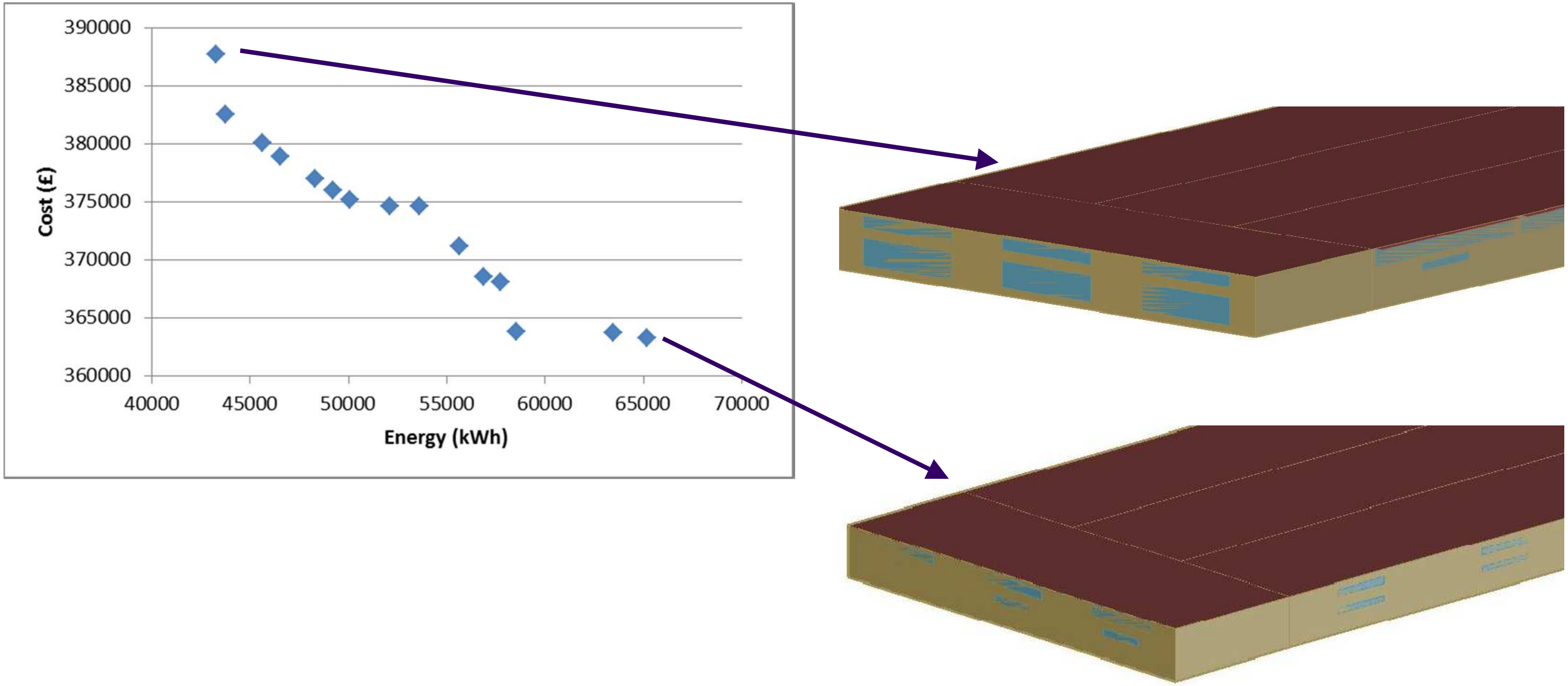
Results



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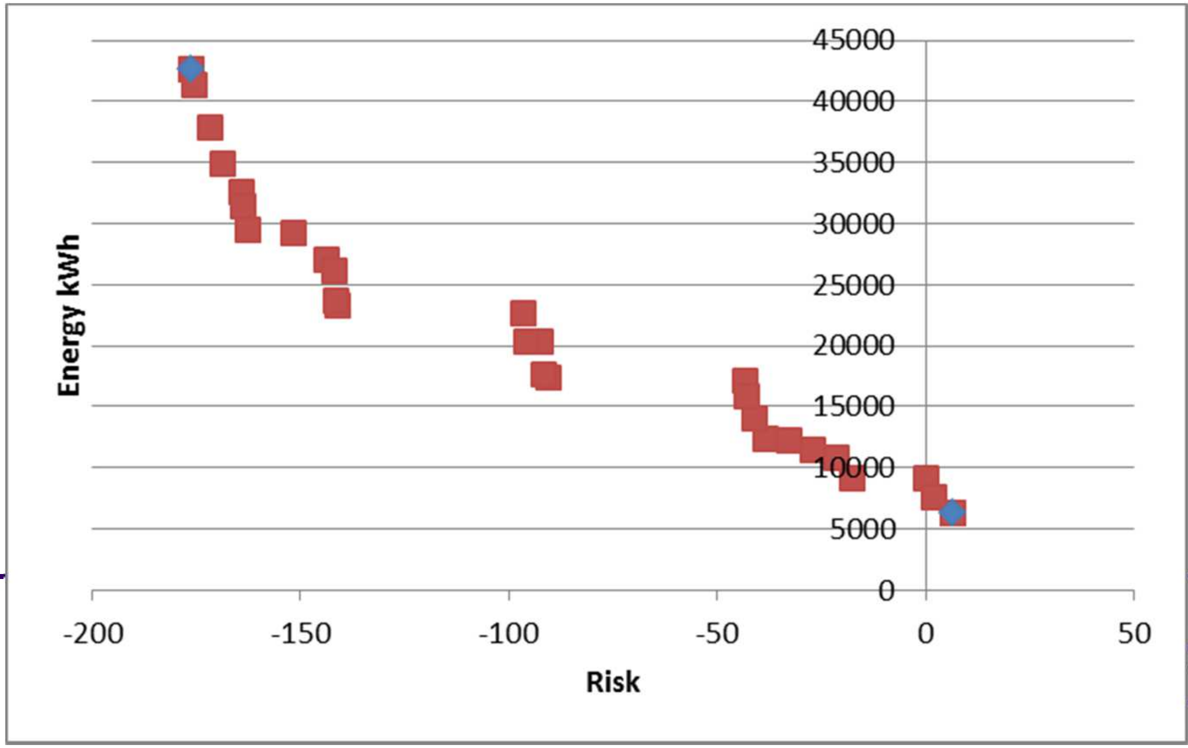
Example 3 : Risk of mould growth

- Optimise HVAC config to identify high risk conditions
- Risk related to long, warm, damp periods
- Hospital ward in Kuala Lumpur



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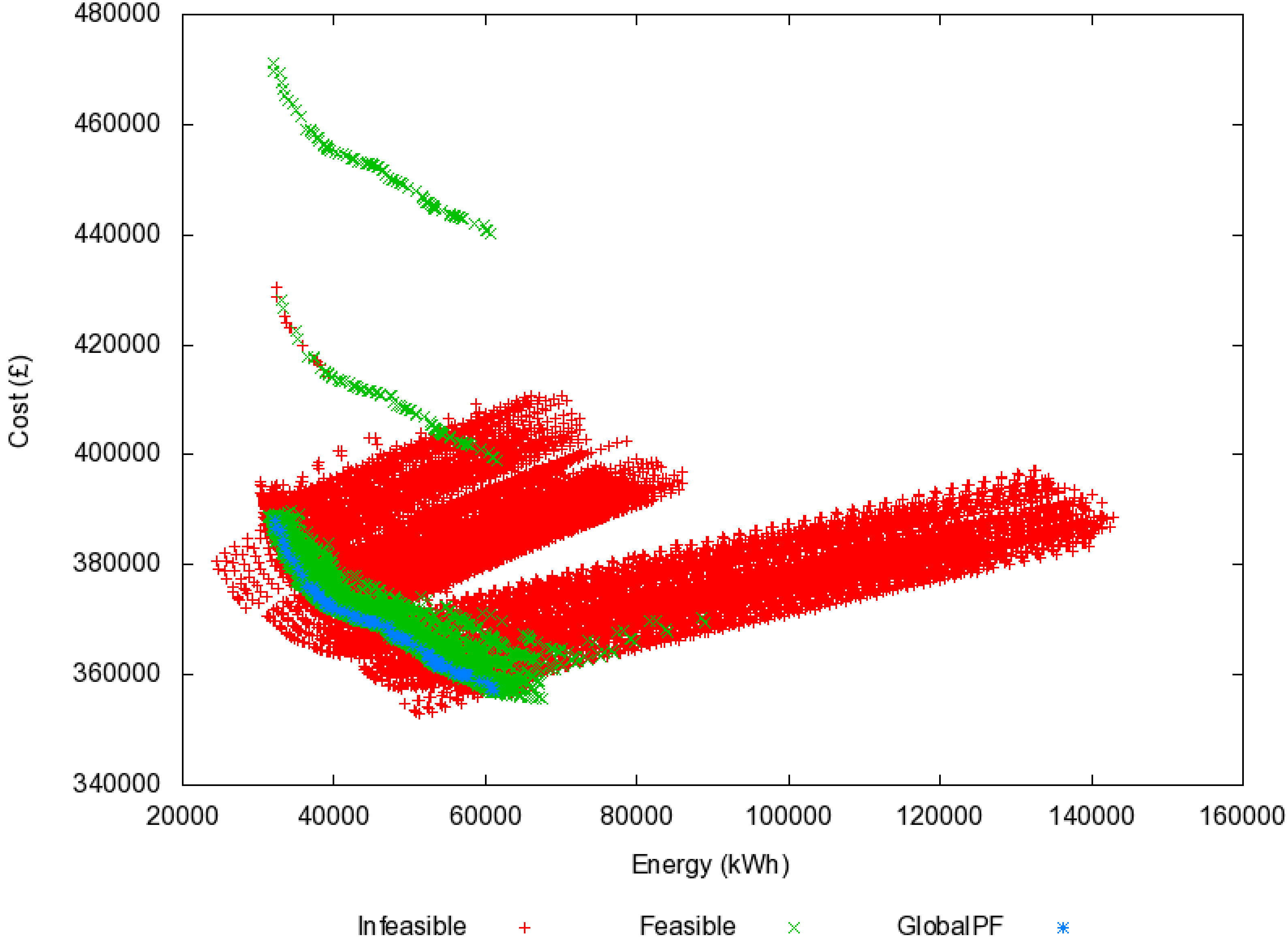
Variable sensitivity

- Aid to decision making
  - What does sensitivity tell us about the problem?
- Observe which variables impact the most
  - Can we ignore some of them to simplify the search?
  - What do we learn about the underlying problem? Can this aid decision making?
- Some are fixed, some vary, both have an impact

Variable sensitivity



rough

Variable Sensitivity

- Jump to IES EP comparison spread sheet
- Energy vs cost for different models
  - Ceiling construction type for IES
  - North glazing area for E+
  - Other glazing areas less important

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Algorithm Improvements

Improvements

- Constraint handling
- Fitness inheritance
- Surrogate model
- Experiments / results

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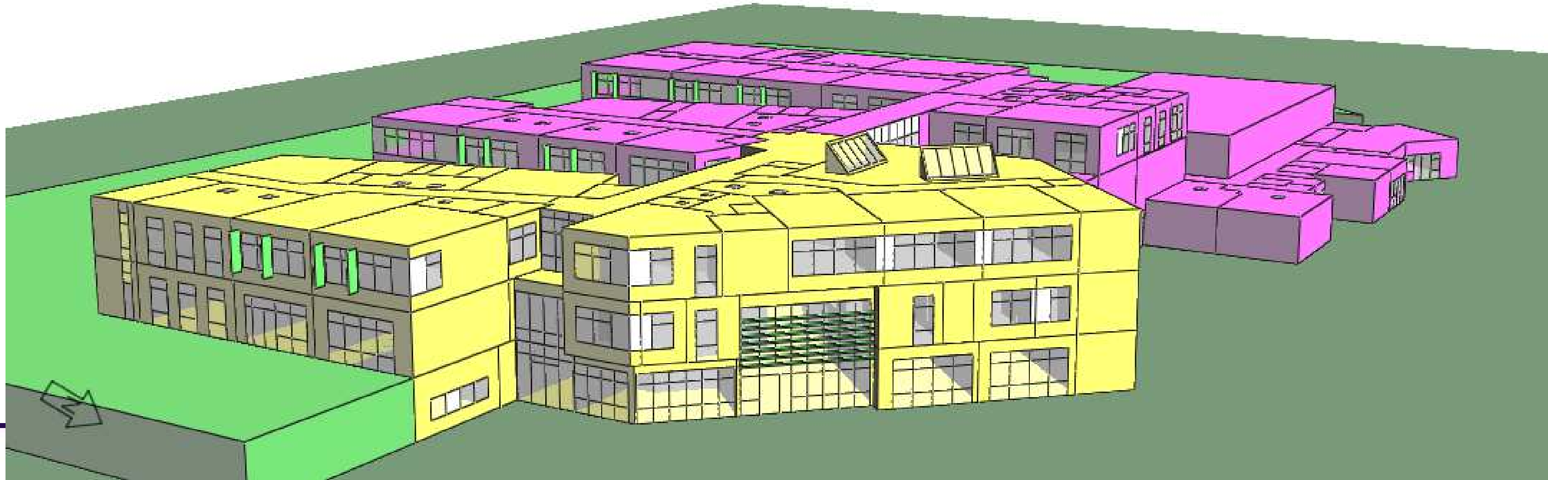
Constraint Handling

- Constraints can be hard to satisfy, and can limit the extent of the trade-off found
- Relaxation – ignore constraints to start with
- Normalise / weighting
  - Constraints weighted equally, or with a bias to meeting harder constraints first
- Include infeasibles in population
  - Allow some infeasible solutions in population
  - Either keep “least infeasible” or “fittest” infeasibles

A problem!

- Typical EA needs thousands of simulations
- Building energy simulation takes 1-2 minutes for example problems
- Larger building or more detailed sim takes longer; also larger search space



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Possible solutions

- Reduce model complexity
- Reduce weather data extent
- Parallel execution / caching solutions
- Fitness inheritance
- Surrogate

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Fitness Inheritance

- Based on the idea that two “similar” solutions will have similar fitnesses / objective values
- After crossover, guess that offspring’s fitness is somewhere between that of parents
- Only inherit sometimes – typically about 50%
- Can weight towards one parent
- How do we deal with constraints?
  - Predict values for each and keep inequality
  - Not ideal!

Fitness Inheritance

0	1	1	1	0	0
1	0	1	1	0	1

Individual	Energy Use kWh	Cost £	Overheating hours (max 30)	Max CO_2 conc. (max 1500)
Parent A	54200	370000	40	430
Offspring	57200	365000	25	330
Parent B	60200	360000	10	230

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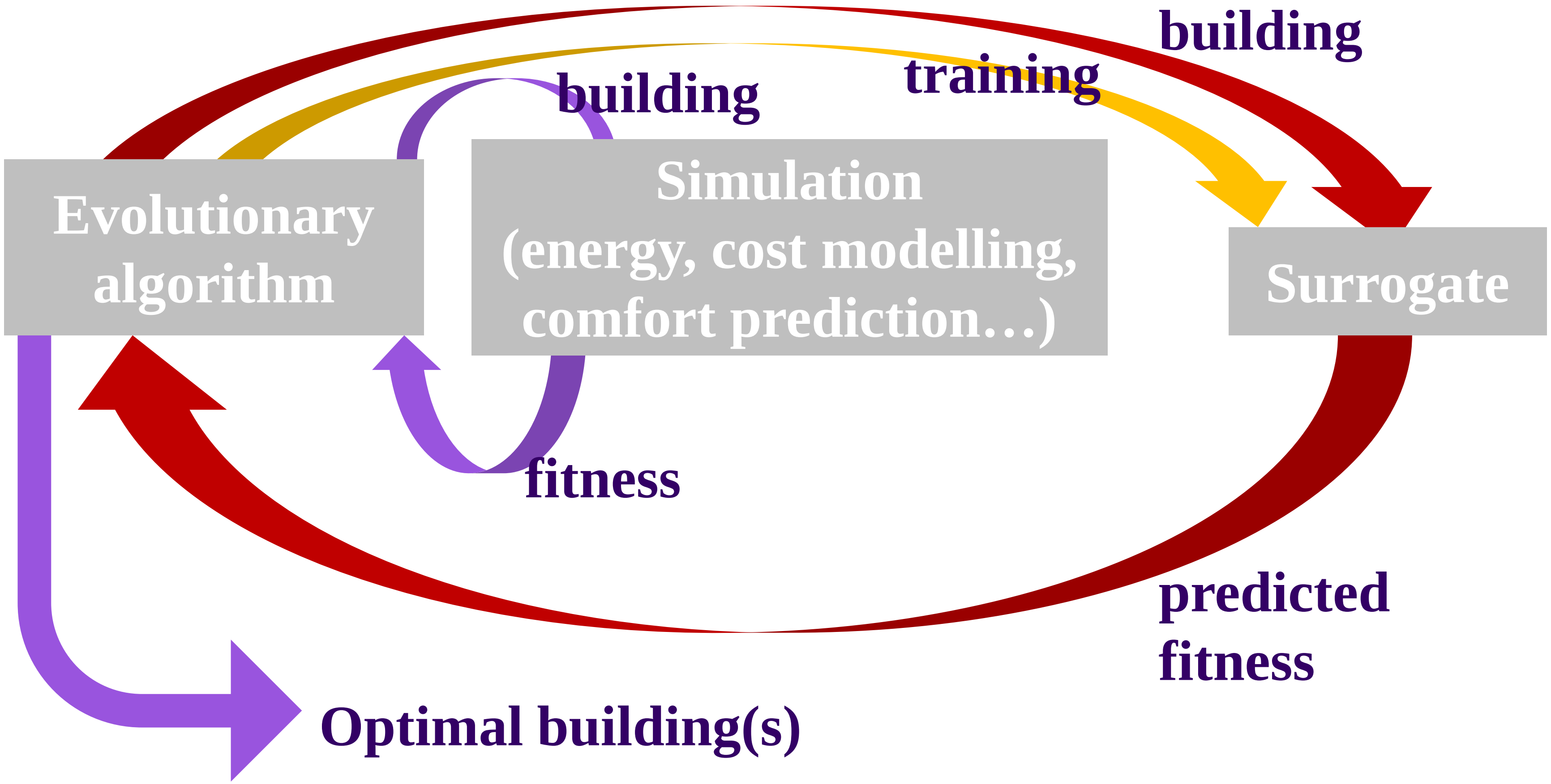
Surrogate Model

- Train a model of the fitness function
- Use the model in place of the FF



Surrogate Model

Plain EA

1. Generate random population
2. Assign a *fitness* to members of the population
3. Choose the best ones and recombine them to produce *offspring*
4. Mutate the offspring
5. Repeat 1-4 until we're done

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Surrogate Model

EA with surrogate

1. Generate random population
2. Assign a *fitness* to members of the population
3. Choose the best ones and recombine them to produce too many *offspring*
4. Mutate the offspring
5. Use surrogate to filter out promising offspring
6. Repeat 1-5 until we’re done

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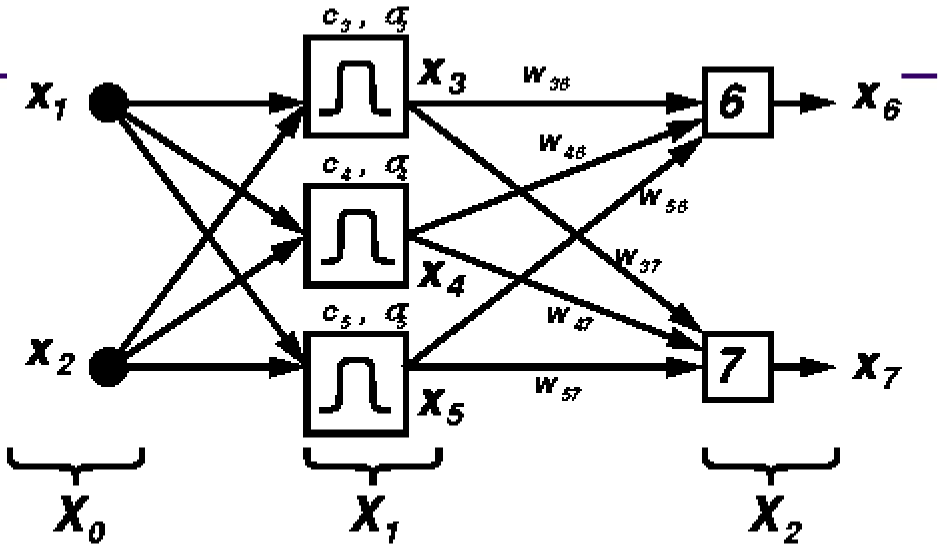
Surrogate Model

- Limited work done with mixture of continuous and discrete variables, and with constraints
- Approach to constraints same as for FI
  - i.e. predict value then do cut-off
- Using a radial basis function network (RBFN)
- Initially tried a single network
  - Had to retrain whole network if part of it poor
  - Now one network per objective or constraint

RBFN



- Feed-forward network
- Input layer: problem vars
- Hidden layer:
  - radial basis functions
  - output similarity to centre
- Output layer:
  - linear weighted sum per objective / constraint
- Distances
  - Euclidian (cont), Manhattan (int), Hamming (bits)

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Experiment

- The 5 zone building problem (energy/cost)
- Run each algorithm config, limit to 5000 evals
- NSGA-II is base-case; calc:
  - mean hypervolume for final sets
  - evals to reach hypervolume target (i.e. the HV reached by NSGA-II in 5000 evals)
  - final archive size (the detail in the trade-off) – this is linked to population diversity

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Results

- Speedup & larger PF size
- Constraints need relaxed in some way

	NSGA-II	+FI	+FI +infeas	+surr	+surr +infeas	+FI+surr +infeas
Evals to mean HV	4191	4080	3015	3998	3662	3740
Success Rate	50	60	70	90	100	75
HV after 5000 evals	0.214	0.216	0.224	0.218	0.220	0.219
Final archive size	23	34	34	23	26	27

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Conclusions

- Optimisation (particularly with EA) a growing area in building design community
- Currently maturing
- Room for improvement
  - Move to concept stage (form / shape)
  - Simulation time a big issue

Questions