Industry challenges in using optimisation tools with IES Optimise as a case study

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ABSTRACT
Optimisation of building design through dynamic thermal modelling is commonplace throughout the design process. However, in general, those modelling the design will generally use an experiential, iterative approach to optimisation. 'Optimise' has been collaboratively developed by lead Engineering solutions provider IES in conjunction with Loughborough University along with partners AECOM, Mott MacDonald, Archial and Davis Langdon. The software offers an automated approach to optimising building parameters such as facade design, fabric performance and HVAC system type for specified objectives such as energy, cost, and carbon. The design solutions are generated using IES's established building performance simulation and an evolutionary optimisation method using Darwinian principles of natural selection pioneered specifically to be used within the simulation by Loughborough University. This paper serves to highlight several industry barriers and challenges for optimisation software such as 'Optimise' to become commonplace in building design. These include:

- Simulation run time
- Complexity of adequately defining the problems to be solved
- Where tools fit in the concept to detailed design process
- Presentation of multi-objective and large amounts of results
- Flexibility of tool functionality for different design market requirements.

Keywords: Optimisation, genetic algorithms (GA), building simulation

1.0 Introduction

Building simulation is commonplace in 21st century building design. More often than not various thermal simulations are undertaken during the design process whether it is for building regulation compliance, thermal comfort or energy predications. Typically each of these processes involves some form of optimisation, albeit often manual and based largely on tacit, experience-informed estimation with little exploration of the entire design space which is computationally expensive [i].

Computational optimisation methods aim to explore a design space in a resource efficient manner with algorithms seeking to navigate quickly to the most appropriate solutions. For multi-objective problems a population of many variable value combinations is used, the aim being to find those for which there is no better performing design across all objectives.

An example of a two objective problem can be seen in Figure 1, in which better solutions have lower objective values (that is, to the lower left of the plot). The algorithm seeks to find points that are non-dominated which forms the Pareto front – a trade-off curve which offers a balance between the two conflicting objectives. Points not on the Pareto front (green) are sub optimal since there is another design solution offering better performance for both objectives.

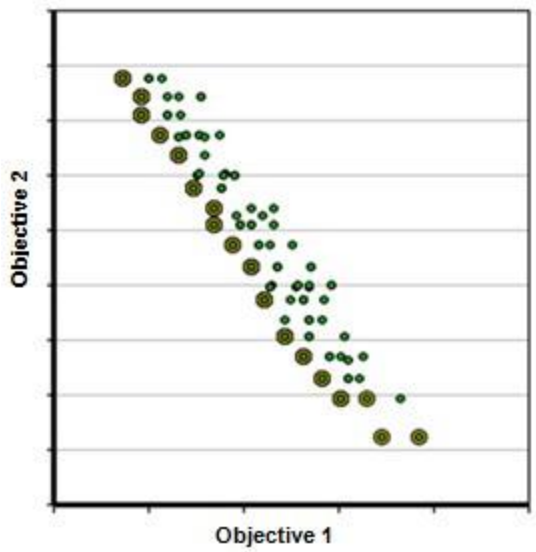

Figure 1: Example of a Pareto front for two objectives. Yellow circles are non-dominated & the green smaller circles are not.

There are many proposed methods for exploring the design space [ii]. Genetic Algorithms (GAs), which use Darwinian concepts of 'evolution by natural selection', are one of the most promising of these methods [iii,iv]. Genetic Algorithms work by maintaining a population of individuals, with the fittest candidate solutions being selected to progress to subsequent generations. Diversity is maintained in the population by means of crossover (combining features of two individuals) or mutation (random changes to an individual). The Non-Dominated Sorting Genetic Algorithm (NSGA-II) algorithm is one of the most popular multi-objective genetic algorithms. Selection is based on non-domination rank which encourages the population to advance towards the optimum front and secondly based on crowding distance (a measure of how closely packed solutions are) which ensures an even spread along the front [v,vi].

Integrated Environmental Systems (IES) <Virtual Environment> have used the NGSA-II algorithm to develop IES Optimise in collaboration with Loughborough University, Archial, Mott MacDonald, AECOM, and Davis Langdon (an AECOM company). The tool aims to bring together previous research in building optimisation tools together into a commercial design tool for use in the typical building design process.

This paper aims to highlight some of the potential challenges in the use of optimisation tools in everyday building design.

2.0 Simulation run time

There are often significant time pressures associated with the building design process, making the time requirements of running many simulations often unfeasible due to the computation and resource intensiveness of the process. As described above optimisation tools aim to minimise the resource intensiveness of the process by using algorithms that aim to navigate quickly and in an automated fashion to the most appropriate solutions. However, even using GA's with multi-objective, complex and discontinuous problems 'convergence' for an optimum solution or Pareto front can still take many hundreds or even thousands of iterations [vii,viii]. This poses a key industrial barrier in utilising optimisation tools such as 'IES Optimise' that use Dynamic Thermal Modelling and where the buildings modelled are often large and complex with many variables.

Figure 2 describes a case study intended to give the reader an indication of the simulation run time for different size buildings, different run time requirements, and different numbers and types of objectives and variables. It is made up of 2 building types – a simple office and a supermarket. Both buildings include comfort cooling and daylight dimming along with gains typical for the given building type. The supermarket includes a large area of glazing on the front typical of large UK supermarkets.
Model 1 is a simple 3 storey open plan office, Model 2 a simple 1 storey open plan office and Models 3 and 4 a typical supermarket. Models 1 and 3 are looking at 2 objectives and variables which are macro scale – that is the values such as orientation, fabric vary at model level not room level. Models 2 and 4 have 3 objectives, one of which is daylight factor and therefore an additional simulation (FlucsDL) is required with every optimisation run. It also has 6 variables, 1 of which is room level – the area of glazing.

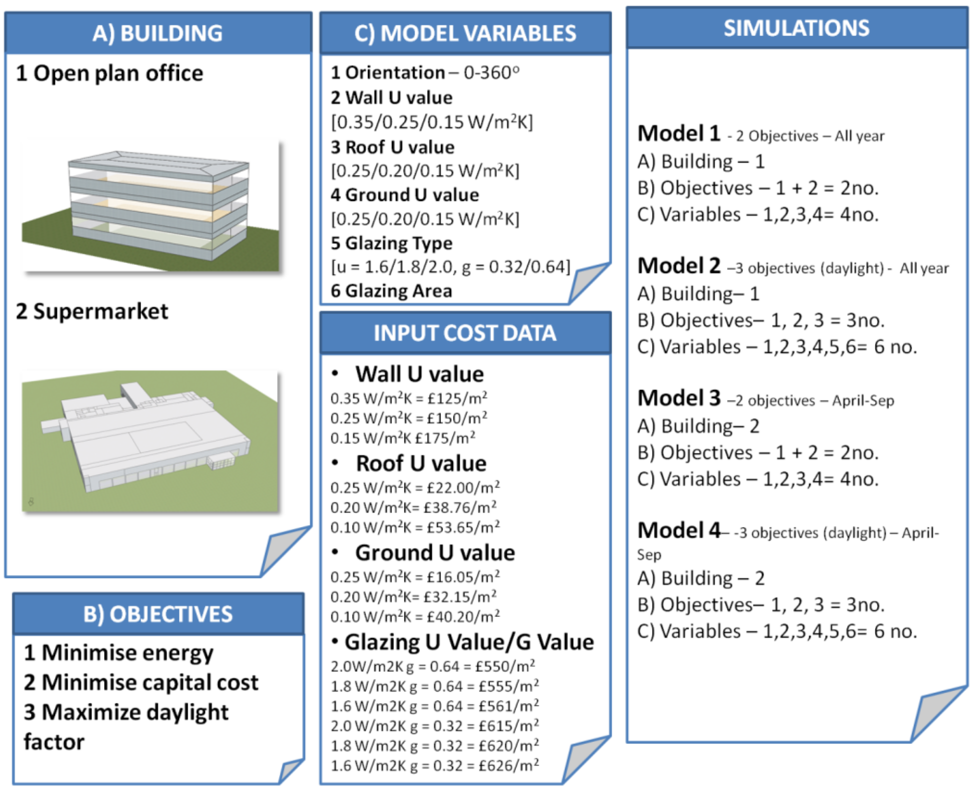

Figure 2: Simulation run time case study

Table 1 shows a variety of numbers that can be drawn from the case study which help to evaluate the differing complexity of the 4 models.

The first column shows the simulation time for 1 simulation to run. It should be noted that model 2 only has 1 floor of the office as opposed to the 3 floors in model 1 and that the supermarket was run for 6 months of the year which halves the simulation run time..

In assessing run time, there are many ways to determine when a GA has *converged*, or settled on an optimum or set of optimal solutions. One approach is to look for the point at which no solutions that offer an improvement are found in a certain number of generations. This point can, however, take a long time to reach, and the GA will likely have found a "good enough" but sub-optimal trade-off containing useful information about the problem much earlier. The comparisons in Table 1 are on the point at which the Pareto front (the set of non-dominated solutions) takes up the whole population. This is the initial point at which an extensive trade-off is achieved. Column 2, 3 and 4 give the number of generations, simulations and simulation time respectively to reach this trade-off. These figures are intended to be indicative, a comprehensive study of run-time would require means taken over multiple runs due to the stochastic nature of GAs.

Table 1 Case study run time analysis

	1	2	3	4
Model	Run time for 1 simulation (seconds)*	Number of generations until fraction of population taken up by Pareto front = 1	Number of simulation runs until fraction of population taken up by Pareto front = 1	Total simulation time until fraction of population taken up by Pareto front = 1 (minutes)
1	34	1	41	23
2	26	11	255	110
3	45	7	99	74
4	180	15	342	1026 [17.1 hours]

*Simulations run on an Intel-i5 running at 2.8GHz with 8GB of memory.

The results of these simulations are discussed in more detail in section 6.0.

The simulation time can be minimised by reducing the complexity of the optimisation problem by simplifying the model into less zones [ix] or running the optimisation tool on smaller models. Reducing the number of variables will reduce the design space therefore undertaking the optimisation process in steps, E.g. optimisation for passive features first and then for HVAC systems, can also be a more effective means of optimisation.

The use of more powerful machines can also reduce the simulation time however dynamic simulation is often limited to running on a only single core, with limited use of multi-threading, due to the difficultly in parallelising the simulation task. The result set for each day is calculated in chronological order so the effects of their predecessors can be accounted for, therefore the improvement due to machine can be limited by 'raw processing power'. However if a population size of 30 is used then the generation could be split across multiple threads and therefore multiple cores.

Cloud computing offers an alternative to more powerful local machines. There are three types of cloud computing: infrastructure as a service (IaaS), platform as a service (PaaS), and software as a service (SaaS) [x]. IaaS offers the opportunity to have access to virtual servers in a service provider's data centre. This can offer significant advantages to companies wishing to use optimisation tools during building design as the increased computer power can be available when required as oppose to companies needing to house such powerful machines in house. Commercial Sustainability Analysis tools currently exist which use cloud computing such as Sefaira[xi]. Given the computing requirements for multi-objective building optimisation it looks highly likely that cloud computing will play a part in its future. However, as above, this approach is only appropriate if the simulation can be split into discrete, parallelisable, tasks.

There are various approaches to the optimisation methodology itself that have been taken in an attempt to reduce the issues relating to the time-consuming optimisation process. These have included 'tuning' the various parameters of the evolutionary algorithm [xii], seeding the starting population with good designs that have been previously identified [xiii], the use of surrogate/meta-models which may be faster to interrogate [xiv].

Surrogate/meta-models can incur a time burden to build, but for more complex models a significant time saving can be realised [xv] and the use of surrogate/meta-models has been suggested for building design optimisation [iv]. Methods have been tested on large commercial buildings using industry software (EnergyPlus) and can be adapted to other models and modelling software [xiv].

3.0 Costing

Optimising with a cost function proves challenging for the evolution of an algorithm due to the discontinuous nature of the function, therefore it is commonplace for building optimisation tools to use derivative free optimisation approaches. However, there are further issues to overcome when using cost as an objective in building design. Optimisation tools offer the user the ability to allocate different costs to different variable values however the relation between the variables and the effect of the buildings cost can be difficult to evaluate successfully. This is due to key factors which affect the cost of a building design being size, shape and layout (e.g. wall to floor ratio), design complexity, specification, location, market, programme/procurement plus other building specific features such as if it is very complex, very tall, special building issues (e.g. security), or large clear spans required. A modeller may look at associated different cost rates for the specific fan power of a system however for the cost to be correctly considered the building specific effect of reducing the fan power may need to be considered. A factor may be derived to estimate the likely cost factor to take into account say larger AHU/duct diameters however the specific costs relating to the project such as if less bends are required to reduce the pressure drops which results in different building routes which could change the clear span of the building cannot easily be considered. However, at early design stages it should be possible for the designers to understand if a design change is likely to increase or decrease the building capital cost.

There is a requirement to match up the ways that a modeller may describe a wall (which would relate to the performance of the wall such as U value, thermal mass) and how a cost consultant would cost different wall construction (which focuses more on material choice, manufacturing ease etc). IES and Davis Langdon (an AECOM company) are currently working to create a database of 'construction types' such as types of wall, roof, ground, glazing with varying performance parameters and their associated costs to help improve the ease of allocating fabric costs. It is likely that a similar process will be required to ensure that there is a robust database of cost ranges for other parameters such as system types so that cost can be used as an objective in building optimisation without the need for a detailed costs analysis. However due to the issues raised above relating to specific project cost variations the use of these cost templates will need to be caveated to ensure the user understands the complexity issues together with guidance on their use.

4.0 Concept vs. detailed design optimisation

Crawley et Al, (2008) considers the capabilities of several design building energy simulation programmes on the market and encourages users to consider adopting different tools for early stage design and more detailed simulations [xvi]. The different requirements for tools at the concept and detailed design stage is likely to make the use of one commercial optimisation package to cover from concept to detailed design challenging. At the concept stage it is more likely that optimisation will be desirable to look at building massing, glazing ratio and fabric performance. As the design progresses off the drawing board decisions such as natural ventilation/mechanical ventilation/air conditioning come into play and at detailed design it is likely that fine tuning of systems is on the agenda such as set points, profiles, and system efficiencies.

Building simulation software that focuses on feedback at the early stages of the building design process tend to be highly visual architectural design tools such as Ecotect for example [xvi]. Software tools that offer an environment for detailed evaluation of building and system designs tend to offer less easy to use interfaces and are less visually impressive tools. Another reason that certain tools are used more at the early design stage is their ease of connectivity to 3D CAD packages such as AutoCAD. Although many advanced simulation packages have plug-ins to enable the import of 3D CAD geometries they can be cumbersome to use with complex geometries.

Tools such as IES <VE> are tools developed for engineers by engineers and therefore it is likely that the development of tools such as these to become effective concept design tools used by architects and engineers alike will be challenging. However this is key for the commercialisation of optimisation tools and therefore the widespread adaptation by industry as often by the time an engineer is involved in the design process many of the initial optimisation variables will have been fixed. The engineering tools do not need to be simplified to appeal to architects but they do need to engage the architect, which is where an important issue lies in how architects and engineers think. New Graduates, emerging from courses such as architectural engineering will help to bridge this gap however architects are essentially visual, spatial, intuitive, lateral thinkers, whose creativity at its extremes is based on breaking rules rather than on following them. Engineers on the other hand tend on the whole to be more analytical, systematic, and process driven. The result of this is that the process of optimisation needs to be simple, graphical and uncluttered and images used wherever possible.

Therefore for a tool to be able to appeal to both architects and engineers it must provide a highly visual interface together with the flexibility to analyse the results at both a numerical and visual level. These issues have been identified throughout the development of IES Optimise and although they are understood they are still to be fully integrated, therefore it is the aim to evolve the tool through progressive refinements to the GUI to become more architect-friendly.

5.0 Data visualisation

Multi-objective building simulation presents a significant challenge in data visualisation where well-presented results are imperative due to the volume and complexity. Evins et al, (2012) looked at multiple case studies in applying visual data exploration processes to sustainable building design [xvii]. It highlighted that feedback in optimisation tools offers a significant barrier to understanding the process, which in turn hinders the use of the results effectively. It concluded that a balance was needed between too much and too little information and, as multi-objective optimisation is often a multi-disciplinary process, the addition of different features from individuals from different backgrounds led to great technical breadth but poor usability in practice.

There are two broad approaches to analysis of results from a multi-objective optimisation process that are quantitative metrics (for comparison of the Pareto fronts or sets) and qualitative analysis (based on observation of trends among the solutions in the fronts). There exist a large number of quantitative metrics designed for comparing Pareto fronts in the objective space. However, while such metrics are useful for comparing the relative performance of different algorithms, they are of limited use for decision-making or analysis of the trends in the solutions as in building design it is important to relate trends in the variables to the trade-off in the objectives [xvii].

Qualitative methods focus on either a visualisation of the Pareto set or analysis of the raw variable values among the Pareto set. Brownlee et al, (2012) discuss several methods of qualitative analysis of optimisation results [xviii]. For 2 objective optimisation problems it is possible to plot the objective values of the Pareto set in 2D [xix] and visually select one “trade-off” solution for analysis [xx]. The 2D plot of the Pareto set can also be simply presented with solutions identified with their variable in a table [xxi] or as rendered images [xxii].

However it is difficult to compare more than two objectives at the same time. Suga et al, (2010), plotted 4 objectives in histograms and used cluster analysis to help trend finding within the variables [xxiii]. Other techniques include using parallel coordinate plots [xxiv] and 3D surface plots as shown in Figure 3[xv].

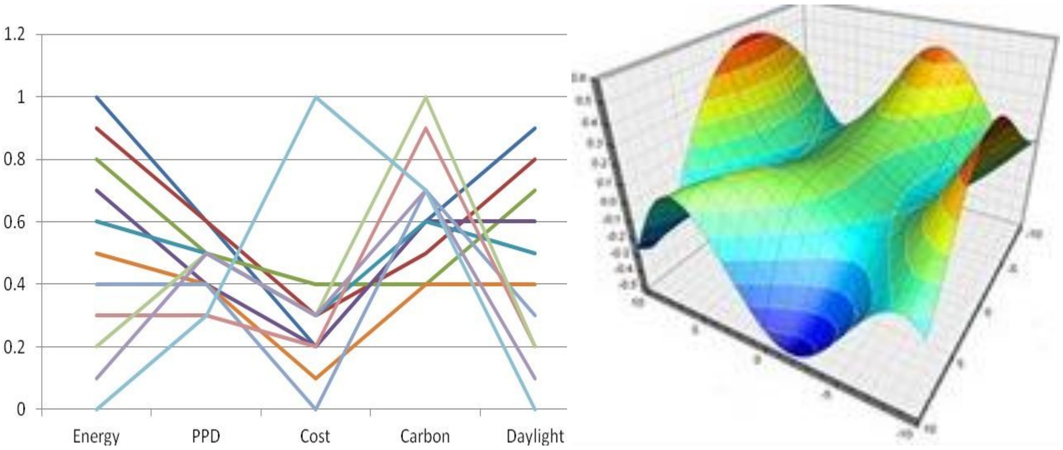

Figure 3: Parallel coordinate plots (left), and 3D surface plot (right)

Brownlee et al, (2012) identified that once the Pareto set is found, the decision making process often takes place entirely within the objective space. Analysis of the front tends to focus on individual solutions rather than trends within the front for each of the problem variables. They proposed an approach that combines a table showing the values for each variable, with a visual bar showing the relative values, combined with the statistical correlation between each variable and one of the objectives. They highlighted the need for both visual and metric analysis of data sets [xviii].

The surface plot shown in Figure 3 offers a highly visual way of viewing the results that is likely to be more appealing to the architect market and client. However further analysis is required to actual understand and interrogate the results. Figure 6 shows an example of an Excel spread sheet using conditional formatting in a similar way to Brownlee et al, (2012) [xviii].

An alternative is to combine this information into a single graphic, as in Evins et al. 2012) which used colours for each variable, allowing the reader to distinguish patterns such as blocks and repetitions [xvii]. Evins et al, (2012) found that the results were often information-rich but not particularly intuitive [xxiii].

6.0 Other possible barriers

During the development of the IES Optimise tool the team often came across issues in correctly setting up problems. It was found that often problems were more complex than they initially appeared, and often a solution would be evaluated and only after the simulations were complete and results available could the issues be seen. This process has highlighted the need for training when new users look at using optimization software for building design together with comprehensive help guides, tutorials and case studies provided by the software provider.

Stakeholder workshops were undertaken throughout the process of developing the IES Optimise tool to ensure functionality was in line with market needs. The initial workshops were held between the consortium team members IES, Loughborough University, AECOM, Mott MacDonald, Archial and Davis Langdon. Several key questions were raised at these workshops as to the fundamental design and operation of the tool such as '*Will the tool be a conceptual design or detailed design tool? What should the variables, objectives, constraints be? Should the optimisation process involve geometrical optimisation? What are the limitations of the process?'* The output of these team workshops was the Requirements Specification for VE-Optimise tool. The specification was for one tool only, which could be adapted to be used at both the concept and design stage. The specification did not include for geometrical modifications during the optimise process but instead the options to model constructions with different shading parameters such as overhangs, recesses or brise soleil. The table below details the variables, objective and constraints detailed in the specification.

Variables	Objectives	Constraints
• Fabric	• Carbon	• Solar gain
• Orientation	• Energy	• Indoor CO_2
• Window area	• Capital cost	• PPD [% people dissatisfied]
• Infiltration	• Daylight factor	• Indoor temperature
• Mech vent rate	• Uniformity	• Capital cost
• Nat vent rate	• PPD	
• Lighting type	• Summer temperature	
• HVAC strategy	• CO_2	
• Set points		
• PV/wind		

Figure 4: Optimise VE Specification - variables, objectives, constraints

Once a working beta of the tool was developed a small stakeholder workshop was held with other IES VE users outside the project team to gather any further tool requirements and general opinion of the tool at this stage. The dominant subject matter during this workshop was the integration of the tool with UK Building compliance check calculations. This highlighted a common issue of good building design vs. carbon compliance and that these are unfortunately not always the same thing. The final outcome of these discussions was that if the tool optimises for carbon it will be working in the right direction to improve carbon compliance, but that full integration at this stage was not possible primarily due to the additional running time requirements. However this is something which may be integrated as the tool develops to offer the flexibility to set a constraint of a building regulations pass.

Optimisation has the potential to offer design solutions which may have not been explored by the design team. Some designers however might see this as a possible waste of time as often some designs are not explored as the designer uses their experience to dismiss options.

Figure 2 shows the setup of 4 models discussed in section 2.0 in relation to simulation run time.

The results can be reviewed to see what options the optimise tool has chosen on the Pareto front. Model 1 is a very simple optimisation and therefore there is limited scope for time reduction through use of the GA as oppose to running the various simulation options and charting the results. However this would require all the models to be simulated and the results collated. The results can be analysed to see if the tool is operating as expected, with Figure 5 showing the Optimise Tool output screen after 352 simulations presenting the trade off forming between capital cost and energy.

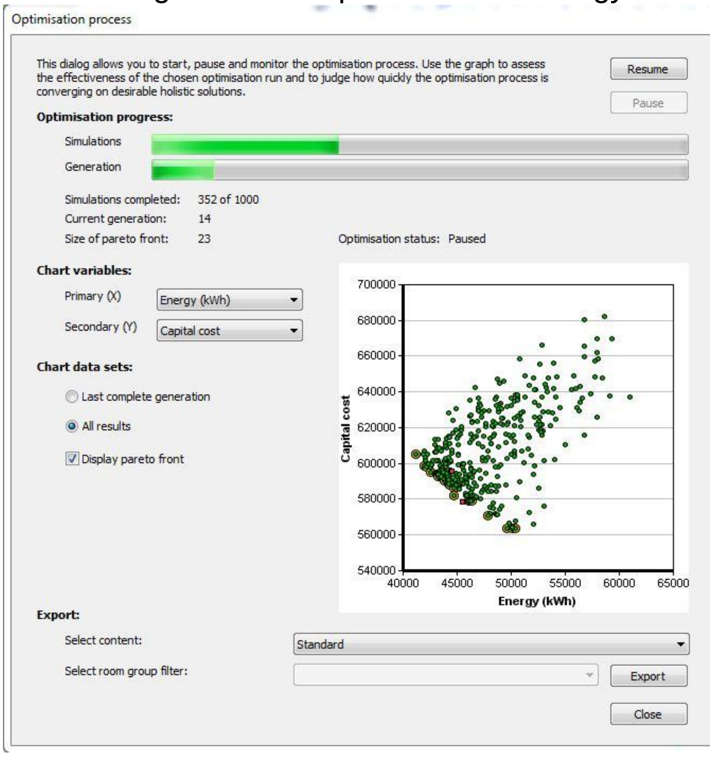

Figure 5: Optimise tool output screen for Model 1

Figure 6 shows how the output of the software can be user formatted and analysed, this can be useful for looking at trends in the data.

Pareto Front	Objectives		Variables			
Eval Number	CAPITAL COST (£)	ENERGY (KWH)	ORIENTATION	WALL	FLOOR	ROOF
122	£ 1,557,790	133,597	0	0.15	0.1	0.1
64	£ 1,557,790	133,597	0	0.15	0.1	0.1
45	£ 1,557,790	133,597	0	0.15	0.1	0.1
38	£ 1,554,168	134,574	0	0.15	0.15	0.1
80	£ 1,554,168	134,574	0	0.15	0.15	0.1
22	£ 1,554,168	134,574	0	0.15	0.15	0.1
44	£ 1,551,089	134,585	0	0.15	0.1	0.15
76	£ 1,551,089	134,585	0	0.15	0.1	0.15
42	£ 1,551,089	134,585	0	0.15	0.1	0.15
16	£ 1,547,467	135,566	0	0.15	0.15	0.15
70	£ 1,547,467	135,566	0	0.15	0.15	0.15
66	£ 1,543,547	136,523	0	0.15	0.1	0.25
125	£ 1,543,547	136,523	0	0.15	0.1	0.25
51	£ 1,543,547	136,523	0	0.15	0.1	0.25
15	£ 1,537,540	137,397	0	0.25	0.1	0.1
95	£ 1,537,540	137,397	0	0.25	0.1	0.1
110	£ 1,537,540	137,397	0	0.25	0.1	0.1
49	£ 1,533,918	138,397	0	0.25	0.15	0.1
115	£ 1,533,918	138,397	0	0.25	0.15	0.1
81	£ 1,530,839	138,399	0	0.25	0.1	0.15
34	£ 1,530,839	138,399	0	0.25	0.1	0.15
27	£ 1,527,217	139,403	0	0.25	0.15	0.15
46	£ 1,527,217	139,403	0	0.25	0.15	0.15
19	£ 1,523,297	140,368	0	0.25	0.1	0.25
32	£ 1,523,297	140,368	0	0.25	0.1	0.25
68	£ 1,523,297	140,368	0	0.25	0.1	0.25
75	£ 1,517,290	141,099	0	0.35	0.1	0.1
97	£ 1,517,290	141,099	0	0.35	0.1	0.1
101	£ 1,517,290	141,099	0	0.35	0.1	0.1
69	£ 1,510,589	142,116	0	0.35	0.1	0.15
47	£ 1,510,589	142,116	0	0.35	0.1	0.15
107	£ 1,510,589	142,116	0	0.35	0.1	0.15
100	£ 1,506,967	143,139	0	0.35	0.15	0.15
114	£ 1,506,967	143,139	0	0.35	0.15	0.15
78	£ 1,503,047	144,112	0	0.35	0.1	0.25
58	£ 1,503,047	144,112	0	0.35	0.1	0.25
109	£ 1,499,425	145,140	0	0.35	0.15	0.25
87	£ 1,499,425	145,140	0	0.35	0.15	0.25
98	£ 1,499,425	146,464	315	0.35	0.15	0.25
0	£ 1,492,179	147,270	0	0.35	0.25	0.25
126	£ 1,492,179	149,234	225	0.35	0.25	0.25

	wall	ground	Roof
0	0.35	0.25	0.25
1	0.25	0.15	0.15
2	0.15	0.1	0.1

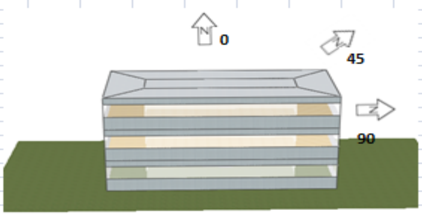

Figure 6: Example formatting of Model 1 results

Key conclusions that can be drawn from the results are:

- Lower energy cases are derived from buildings where the long length forms the South and North facades with the shorter lengths forming the East and West. This is generally expected to be the best orientation in the UK for low energy solutions.
- Based on the costs, fabric parameters entered and UK climate the lower U values (rate of heat loss) result in lower energy and higher capital cost as expected.

Simple simulations such as this can be used to see the range of energy/cost values from a variety of performance fabric and then used to create constraints as a post processing exercise based on other factors such as project budget and energy targets as shown in Figure 7.

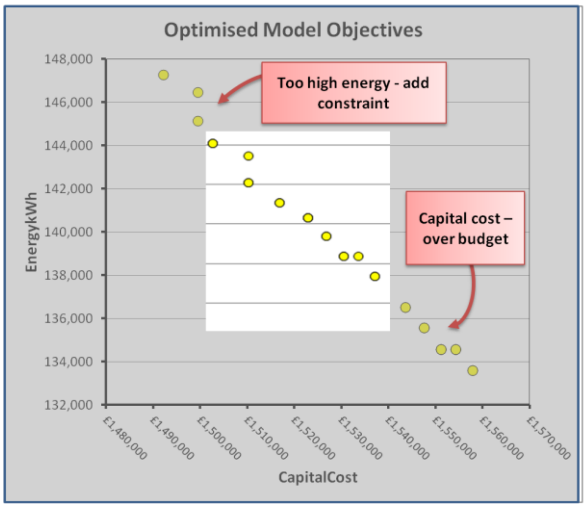

Figure 7: Post processing addition of constraints

Model 2 is the simple office with 3 objectives – minimise cost, maximize daylight and minimise energy. Figure 8 shows the output screen of the Optimise tool after 352 simulations showing the trade off between capital cost and energy.

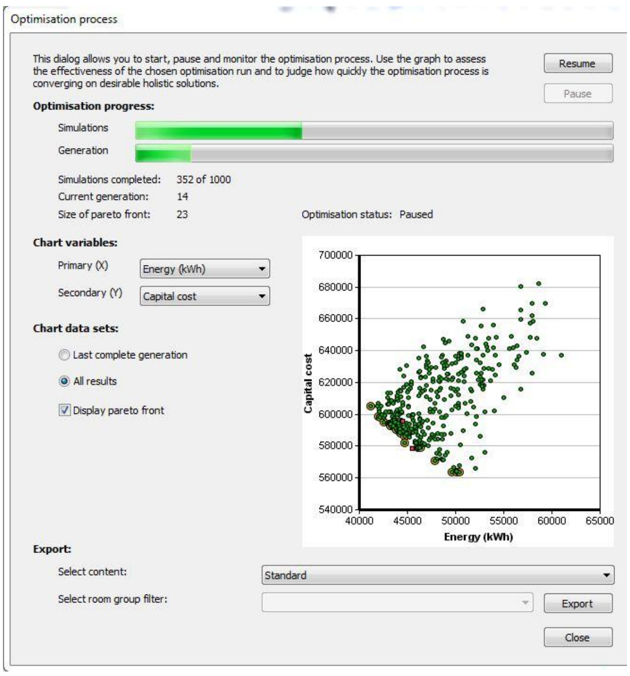

Figure 8: Optimise tool output screen for Model 2

The data can be formatted and analysed in a similar way to that shown in Figure 6. After analysing these results the following initial trends could be seen:

- As energy increases capital cost decreases however daylight factor does not follow the same relationship
- Reducing glazing area reduces cost and energy and therefore is generally driven down to the minimum for all solutions as a good daylight level can be achieved even at 20% glazing area given the building shape and layout.
- The majority of optimum solutions are at 0 or 45 degrees where the length of the building is on the East-West axis North East/West- South East/West.
- The daylight factor varies based on glazing area and glazing light transmittance.
- The heating is more dominant than the cooling energy in the building as improving the U value of the fabric has a noticeable effect on the energy however solar control and low e glass solutions are mixed in throughout the solutions.
- Solar control glazing is generally less popular in the optimum solutions probably due to the glazing having been driven down to 20% of the façade.
- The North glazing is always high thermal performance and low e glazing to maximise daylight
- The majority of the solutions have a U value of 0.15W/m^{2}K for roof and ground with very few solutions pushing the façade down to this level.
- The cases where the glazing is greater than 20% have additional glazing on the east and tend not to use the solar control glazing.

Model 3 is supermarket with 2 objectives – minimise cost and energy. Figure 8 shows the output screen of the Optimise tool after 144 simulations showing the results of the simulations in terms of capital cost and energy.

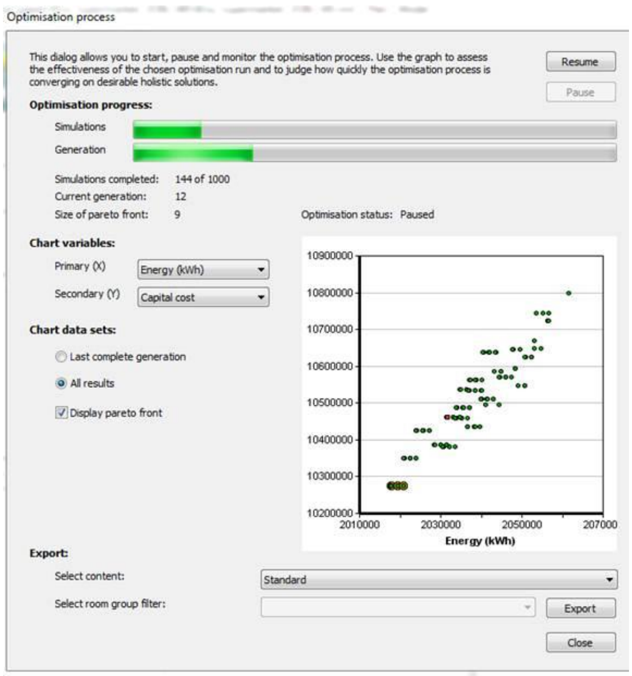

Figure 9: Optimise tool output screen for Model 3

After formatting and analysing the data in a similar way to described previously the following conclusions can be drawn:

- Worst energy solutions are when the fully glazed store front is South-West and the best energy solutions are when the store front is at North West.
- The solutions which are clumped together in Figure 9 showing the same cost but different energy are where the orientation is the only variable change.
- The cooling load is dominant in this building due to the high internal gains from lighting as the “optimum” solutions presented are with the higher U values which allow these high heat gains to escape. The higher U value fabric is also lower cost and that is why a trade-off curve has not presented itself in a similar way to Model 1 and Model 2.

Model 4 is the supermarket with 3 objectives – minimise cost, maximize daylight and minimise energy. Figure 10 shows the energy vs. capital cost graph after 296 simulations.

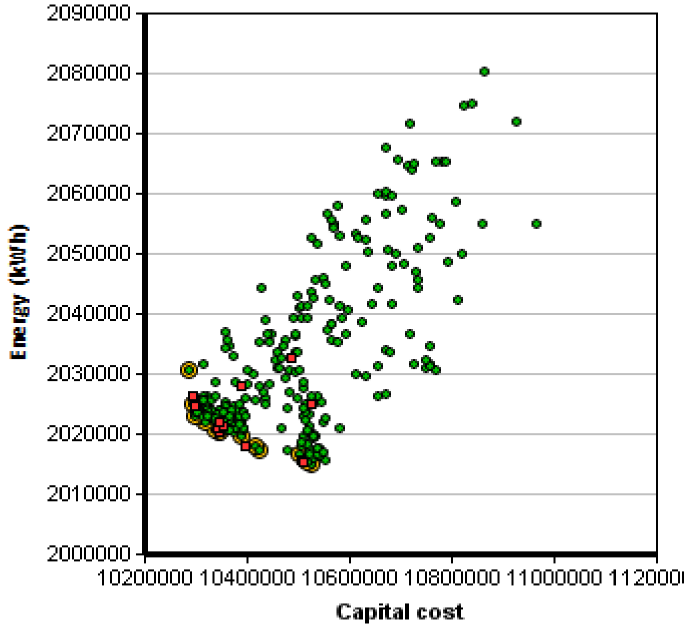

Figure 10 Optimise tool energy vs. capital cost graph for Model 4

After formatting and analysing the data in a similar way to described previously the following conclusions can be drawn:

- As with model 3 due to the dominance of the cooling load all the solutions on the Pareto front were using the higher opaque U values. This also followed through to the glazing U values with the lower energy cases choosing a U value of 2W/m^{2}K for the store front glazing.
- Both energy consumption and capital cost objectives are highly dependent on the area of the store front glazing. The Pareto front forms with the outer points at 15% glazing with a g value of 0.64 (lowest cost/highest energy) and 80% glazing with a g value of 0.32 (highest cost/lowest energy).
- In the supermarket the lower energy cases were with a large area of glazing on the store front (75-85%). As the other sides of the store were opaque the large percentage area of the store front reduces the lighting load in the space. Although the solar gain also increases the cooling load and subsequently the cooling energy

the reduction in lighting energy outweighs this and results in lower energy overall.

It is hoped that the four models detailed in this paper give the reader an idea of the types of result which can be seen when running and optimisation simulation using optimisation tools such as IES Optimise.

7.0 Conclusion

It is very easy for the building industry to see optimisation as a 'one-click' stop for high performance building design. However, as this paper has highlighted there are several complexities in the process that show that this is not the case.

Simulation run time is still a key barrier and it is likely that initially the tool will be used by consultancies that have the computing power such as IES themselves.

It is difficult to create a tool that can capture the subjective nature of building design and therefore the designer will still be required to set up the problem to ensure correct boundaries for the algorithm and also interpret the results to find trends in the data. Some methods have been identified here though which could help with the interpretation of the data – it is likely that some of these methods will be required for multi-objective complex buildings to be simulated as without this it is unlikely the designer will have the time to decipher the results.

IES Optimise is currently in beta testing and it is expected that the first couple of years of its use will see many revisions as usability and functionality improves following feedback from users.

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