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DESIGNING-IN PERFORMANCE: EVOLUTIONARY ENERGY PERFORMANCE FEEDBACK FOR EARLY STAGE DESIGN

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ABSTRACT

A framework entitled Evolutionary Energy Performance Feedback for Design (EEPFD) was developed to mobilize the potential of multidisciplinary design optimization (MDO) towards solving current obstacles between design and energy performance feedback. However, EEPFD needs to be applicable to the early stage design process where it has the potential for the greatest impact on the overall building lifecycle performance. This paper focuses on examining two criteria identified as necessary components to confirming the validity of EEPFD prior to EEPFD's application to the actual design process: 1) the ability to accommodate varying degrees of geometric complexity; and 2) the ability to provide a continuing improved solution space. Through 12 hypothetical cases, the research confirms that EEPFD meets these criteria and therefore is suitable for further exploration in application to the early design process. Effective applications of EEPFD to the early stages of design are also explored and discussed.

INTRODUCTION

With the advancement of current technology, Computer-Aided Design and Engineering (CAD/CAE) tools enable architects and engineers to pursue higher performance in building design by simulating different aspects of building performance, such as financial, structural, energy, and lighting efficiencies. However, due to tool interoperability, design cycle latency and domain expert disconnection, these performance feedbacks rarely can support design decision making during the early stage of design where such decisions have a disproportionate impact on the overall building performance versus later design stages.

The use of multidisciplinary design optimization (MDO) to provide performance feedback for assisting with design decision making has demonstrated a potentially effective means to overcome the limitations of current performance-based design processes. This approach has shown reductions in design cycle latency, resolutions of interoperability issues, and an ability to provide designs with improved performance results. However, current attempts have yet to fully explore the applicability of this approach regarding the unique demands of early stage design where rapid exploration of variety and alternatives within designated time constraints is necessary for the pursuit of "designing-in performance."

The concept of "designing-in performance" is defined in this research as the idea of utilizing performance feedback information for design exploration and subsequent decision making under the assumption of pursuing higher performing design. In order to evaluate the suitability of applying MDO to this concept for the purpose of early stage design decision making a design framework, Evolutionary Energy Performance Feedback for Design (EEPFD), was established. EEPFD utilizes the two key components of MDO, a multi-objective optimization algorithm and parametric design methods, to pursue improvement in the performance of energy, financial, and program qualities of a design. The intent of EEPFD is for designer use during the conceptual stage of design where geometric components and massing have not been finalized.

In order for EEPFD to be considered a valid method of incorporating MDO to pursue "designing-in performance," for early stage design, it must first be able to provide a solution space with an improved performance in a timely manner. In addition, EEPFD must also be adaptable to a wide spectrum of design scenarios while continuing to provide an improved performance solution space as desired. The objective of this paper is to explore EEPFD's ability to meet these two prerequisites.

PRECEDENTS & POINT OF DEPARTURE

In this section, the research presents current issues and obstacles between the design and energy simulation domains while synthesizing the needs of a "designing – in performance" environment. The research then moves on to review precedents' potential solutions and summarize the gaps of current attempts. Finally, the point of departure of this research is identified.

Current Barriers towards Designing-in-Performance between Design & Energy Simulation Domains

While the overall performance of buildings is greatly impacted by design decisions made during the early stages of design, unfortunately, design professionals are often unable to adequately explore design alternatives and their impact on energy consumption upfront (Crawley et al., 2008). Conventionally adopted performance based analysis methods have been shown by prior studies to be ill suited in their ability to support early stage design decisions due to time limitations (Flager and Haymaker, 2007). In addition there is often the issue of environmental simulation software needing to be operated by experts due to the typically specialized nature of these tools. Other issues are also presented repeatedly in precedents, such as tool interoperability, intensive analysis time requirements, and limitations of design cognition and complexity can be considered as contributing factors to design cycle latency (Oxman, 2008, Augenbroe, 2002, Attia et al., 2012). Consequently, performance assessments are typically made after the initial design phase, where the analysis is performed on a very limited set of design alternatives rather than to support early stage design decisions where a broader range of possibly more optimal solutions may exist (Radford and Gero, 1980). In addition, designers must often balance the needs of multiple competing objectives and there is currently a deficit in providing the means of assisting in identifying the best fit through an understanding of trade-offs across energy performance and other necessary domains.

To address these issues it has been identified that a design framework and tool should provide 1) rapid generation of design alternatives; 2) rapid evaluation of design alternatives; 3) trade-off analysis for competing criteria; and 4) a search method to identify design alternatives with better fit performance (Augenbroe, 2002). These requirements are reflected in a trend of recent development efforts regarding the domains of design and performance feedback.

Potential Solutions through MDO Precedents

Recently, multidisciplinary design optimization (MDO) has drawn the attention of the AEC industry as being capable of providing potential solutions to overcome obstacles existing between design and other performance analysis domains. The original MDO methodology intent is to “exploit the state of the art in each contributing engineering discipline and emphasizes the synergism of the disciplines and subsystems (Sobieszczanski-Sobieski, 1993).” After years of development, “MDO methodology evolved means by which such concerted action may be implemented in a systematic and mathematically-based manner (AIAA, 1991).” This approach has been successfully adopted by the aerospace industry and other engineering fields, but has only just begun to be explored in its applicability to the AEC field. Current MDO precedents in the AEC industry have two main foci: multidiscipline collaboration and multi-objective optimization (MOO) procedures. A focus on the collaboration aspects of the MDO method between multiple disciplines explores the actual collaboration method among various domain experts (Toth et al., 2011, Holzer, 2010). The other focus is on the application of MDOs’ procedure to explore multiple, and often competing, objective optimization through the incorporation of parametric modelling and multi-objective optimization algorithms. This research focuses on this latter aspect of MDOs. While the collaborative component is not explicitly addressed, or excluded, by this research there is an assumption that through later development the collaborative component can be re-emphasized.

Other representatives of research in this second area of MDO focus include a building design precedent investigatig the application of a multi-objective genetic algorithm for finding the optimal in the trade-offs between capital expenditure, operation cost and occupant thermal comfort in building design (Wright et al., 2002) and a MDO in a building design setting with thermal, structural, financial and environmental performance evaluation by integrating all the platforms via an IFC scheme (Geyer, 2009). Other applications of MDO can be found in optimizations of structures and energy performance for classrooms (Flager et al., 2009), energy and thermal confort in residential buidings (Magnier and Haghighat, 2010) (Asadi et al., 2012) , and window sizing and placement for maximizing indoor comfort (Suga et al., 2010). These precedents all demonstrate the potential ability of MDO to assist in identifying higher performance solution sets among multiple competing criteria.

Gap Analysis and Point of Departure

Research precedents have demonstrated the potential of adopting MDO to provide a performance feedback loop for supporting early design stage decision making. However, precedents exploring MDO in the AEC field have typically employed simplified geometry and have placed more emphasis on structural or mechanical systems. Where the energy performance domain has been included for optimization the relationship between design form and energy performance has been largely excluded. Furthermore, the application of these precedents’ subject of interest to the overall design process remains largely unexplored.

In response to this gap in existing research an early stage design framework, EEPFD, was developed.. EEPFD incorporates both conceptual energy analysis and exploration of varying degrees of design forms for providing early stage design performance feedback. EEPFD utilizes a prototype tool (H.D.S. Beagle) which enables the coupling of parametric design with multi-objective optimization (Gerber et al., 2012). Also included in the multi-objective optimization process are spatial programing and financial performances for consideration in performance trade-off studies.

The paper focuses on exploring the validity of EEPFD as a means of pursuing "designing-in performance" for the early stage of design prior to a full design process case study. The two identified critical criteria are 1) the ability to provide a solution space with an improved performance, as defined by this research, in a timely manner; 2) the ability to be adaptable to a wide spectrum of design scenarios while continuing to provide improved performance solution spaces as desired.

Success in this research is not defined as the reaching of an optimal solution providing the mathematically defined ideal convergence as typically intended in other MDO applications. This is due to the issue of time constraints usually dominating the stopping point of the early design exploration process and the inherent nature of design decision making being based on trade off and often subjective choice. Considering this issue of time the goal of EEPFD is to provide a design alternative pool with improved performance by which to support informed design decision making. Therefore, success in this research is defined as the observation that EEPFD consistently provides a design alternative solution pool with measurable performance improvement within the time allowed.

INTRODUCTION OF EEPFD

EEPFD stands for Evolutionary Energy Performance Feedback for Design and is a MDO based design framework that was developed in concert with to the prototype tool, entitled H.D.S. Beagle, to implement a customized GA-based multi-objective optimization (MOO) algorithm. H.D.S. Beagle was developed as a plugin for Autodesk® Revit® (Revit) (Autodesk, 2013b) which integrates Autodesk® Green Building Studio® (GBS) (Autodesk, 2013a) and Microsoft® Excel® (Excel) (Microsoft, 2013) to generate the desired automation and optimization routine.

H.D.S. Beagle Introduction

Revit is a building information modeling platform with parametric capabilities enabling designers to define their geometry while providing a series of parameters that impact the development of varying geometric configurations. This platform also serves as an insertion point for the energy settings necessary for a conceptual energy analysis through GBS. GBS is a web-based energy analysis service that serves as the energy simulation engine for the prototype. Excel provides not only a means of containing the financial parameters and formula, but also as a user interface proxy in which designers can set up design parameter ranges of interest, constraints, spatial program parameters, and the spatial programing compliance formula. The three objective functions can be formulaically expressed as Equation 1 - 3:

$$S_{obj} = Max.\ SPCS \quad (1)$$

$$E_{obj} = Min.\ EUI \quad (2)$$

$$F_{obj} = Max.\ NPV \quad (3)$$

Where

S_{obj} = *Spatial Programming Compliance Objective Function*

E_{obj} = *Energy Performance Objective Function*

F_{obj} = *Financial Performance Objective Function*

SPCS = Spatial Programing Compliance Score

EUI = Energy Use Intensity

NPV = Net Present Value

The spatial programing compliance (SPC) score evaluates the meeting of the project defined program requirements by a generated design option. This is defined by the user as the desirable amount of specific types of programming in square feet. The energy use intensity (EUI) value evaluates the estimated energy performance of the generated design option. This is provided directly through the schematic energy analysis done by GBS. Finally, the financial performance, net present value (NPV), is calculated according to the definition of the financial pro forma for each generated design option from relevant information extracted from both the generated geometry and the produced energy simulation analysis. Construction costs are derived from combining calculated material quantities from the generated geometry with their respective user provided per unit prices. Operation costs are calculated by combining expected fuel and electricity usage from the energy simulation results with per unit costs provided by the user. Finally, prospective income is derived from a user defined value for each square foot of specified program combined with the calculated program quantities from the generated geometry.

After the SPC, EUI, and NPV objective scores are calculated for each design iteration H.D.S. Beagle proceeds to rank all design iterations according to the Pareto ranking method based on their scores. In the Pareto ranking method, the Pareto-Dominance (p<) concept is used to compare two individuals. The superiority of one individual over another is decided by comparing the two individuals' performance across the multiple objectives. Equation 4 is the definition of the Pareto-Dominance as applied to the previously defined three objective functions of this research:

$$\forall \in \{S_{obj}, E_{obj}, F_{obj}\}\, f(solution_1) \leq f(solution_2) \quad (4)$$
$$\exists \{S_{obj}, E_{obj}, F_{obj}\}\, f(solution_1) < f(solution_2)$$
$$\rightarrow solution_1\ p<\ solution_2$$

According to this definition, if $solution_1$ has superior performances than $solution_2$ in all three objectives (denoted by $solution_1$ p< $solution_2$), then $solution_1$ dominates $solution_2$ in the order of rank. For example, if individual A has the objective scores of (94, 160, 65) and individual B has the scores (97, 102, 82) then individual B would be considered dominant, or more "fit.", . However, if individual C has the objective scores of (90, 104, 85) and individual D has the scores (98, 153, 90) then individual C and D would be considered incomparable or unable to dominate each other. In this case the ranking of an individual implies the number of individuals within the same pool which are considered dominant to the individual in question. Therefore, the fittest individual in a set of offspring would be assigned the ranking of 1 with all other offspring following in suit. Consequently, higher ranked individuals have a higher probability to be selected as a parent for the reproduction process. The specific Pareto ranking method adopted by this research can be found in Fonseca and Fleming's Pareto ranking method and expressed as Equation 5 (Fonseca and Fleming, 1993).

$$Rank_j = 1 + Num(Individual_{dominated}) \tag{5}$$

A more detailed description of the adopted method which drives EEPFD and the automated engine of H.D.S. Beagle can be found in previously published research (Gerber et al., 2012).

EEPFD Simulation Process

EEPFD can be described through the six steps commonly observed in a simulation process, as illustrated in Figure 1. The implementation of these six steps are described in the following:

1. Step 1 Generate Design: For this process there are two subcategories: the generation of the initial design and the generation of design alternatives. The initial design is developed through the preparation of the initial executable design and constraints file according to the designer driven project requirements. At this point the initial geometry, applicable parameters, site information, parametric ranges of interest, program requirements, and available financial information are provided by the user. Design alternatives are then automatically generated by H.D.S. Beagle according to the manipulation of the specified parameters within the user defined ranges.
2. Step 2 Transfer Model: The integrated platform enables the direct translation of the design geometry and related energy settings into the energy simulation engine provided by GBS. As a result, an analyzable energy model can be obtained directly thereby proceeding with the energy simulation without additional modification of geometry or energy related attributes. In this process H.D.S. Beagle automatically converts and sends the design alternative to the GBS server to request and obtain a conceptual energy analysis.
3. Step 3 Modify Energy Model: This step is bypassed since the model transfer to GBS is automated by Revit, which is unavailable through most non-integrated platforms.
4. Step 4 Run Analysis: In this step the energy model of the design alternative is sent to GBS for analysis. When automated through H.D.S. Beagle this step is automatically performed through Revit.
5. Step 5 Evaluate Results: This step has 2 stages. The first stage is the calculation of the objective function scores for each alternative once the energy analysis is available. H.D.S. Beagle automatically extracts relevant information from the energy analysis results along with relevant information from the design model to calculate the SPC and NPV scores of the design alternative. The EUI score is provided directly from GBS. The second stage is to Pareto rank each design alternatives according to the calculated objective scores.

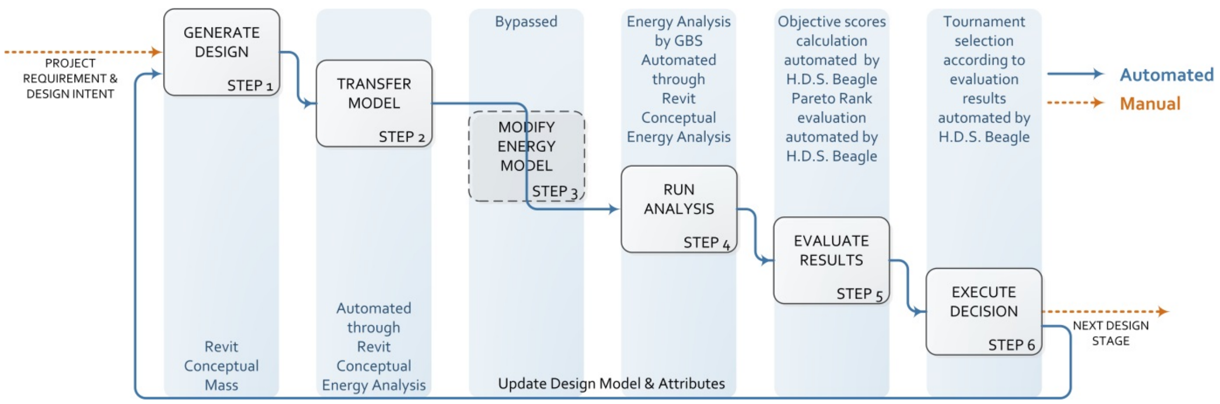

Figure 1 EEPFD's six-step process for integrating design and energy simulation

6. Step 6 Execute Decision: In this step, there are two aspects of the necessary decision making. First, is with regards the decision making mechanism encoded within H.D.S. Beagle during the automated loop. During a GA run the Beagle utilizes tournament selection to identify and select parents from a pool of design alternative to breed the next generation of design alternatives, cycling through the process until the stopping criteria met. Second, once the automated decision making is completed there are two ways to proceed: 1) the user manually implements changes in the initial design or constraints file of the executable design file based on acquired simulated results, which would also suggest another optimization run; or 2) a design alternative is selected based on the multi-objective trade off analysis provided by the Beagle and the design proceeds to the next stage of development.

EXPERIMENT DESCRIPTION

As previously established, any framework being considered as a potential solution for implementing a GA based MOO method for the purpose of "designing-in performance" must be versatile enough in nature to be adaptable to a wide range of design problems. The purpose of the validation process described here is to determine whether EEPFD meets this criterion and can provide improved performing results in greater numbers in a timely manner to support design decision making. To pursue this, a series of design scenarios were generated by the research to represent the varying complexity in both geometry and program requirements that may be encountered though real world design problems or in a design studio setting.

For this experiment, 12 design scenarios were prepared for testing by EEPFD. In this research, a design scenario is defined as a hypothetical design problem consisting of parametrically defined characteristics that include but are not limited to space programing type, driving parameters, driven parameters, project size, and project requirements. Geometric complexity is explored through a range from a simple orthogonal box to towers with double curvature and twisting factors. The program complexity range explored includes scenarios with single use requirements, such as an office building, to mixed-use space including underground parking, retail, hotels, etc. Each scenario utilized the same hypothetical site located in West Hollywood, CA thereby providing consistent site related information and climate data to each hypothetical scenario. The comparison of the full spectrum of geometric, program, and design complexity explored is provided in Figure 2.

This research proceeds to categorize the types of measurements to be collected into three categories: design problem, process, and product. Measurements falling into the design problem category are values collected regarding the physical aspects of the design and are further divided into two subcategories: project complexity and design complexity. Project complexity refers to the project size as measured in square feet and the number of types of program spaces, such as parking, commercial or residential, that are included within the design problem. Design complexity refers to the amount of surfaces i.e. tesselation required to be included in the energy model along with the number of available parameters as provided by the design problem. Process based measurements are divided into two subcategories: speed and documented GA settings.

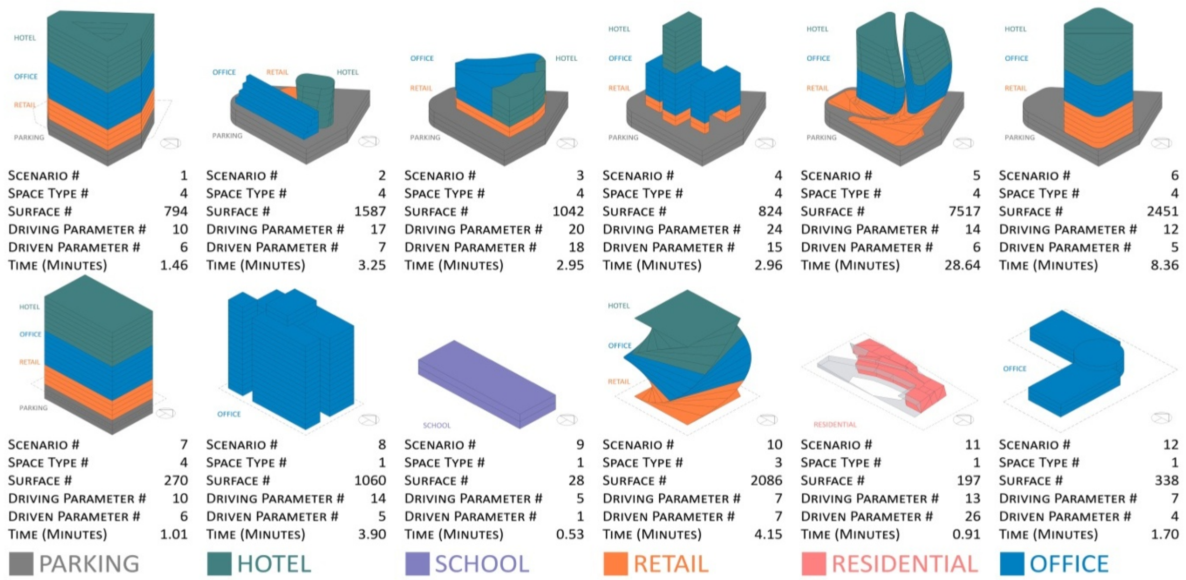

Figure 2 The summary of the 12 hypothetical design scenarios tested by EEPFD.

Speed is in reference to the measured time experienced in running the energy analysis. The GA settings refer to the values documented for a series of user adjustable characteristics of the GA including the initial population size, crossover ratio, mutation ratio, population size, selection size, and maximum iterations. Product measures focus on evaluating the quantity and quality of the resulting solution space. Quantity refers to the number of design iterations generated over an 8 hour work period. Quality is in reference to performance ranges of the resulting solution space as defined by EUI, NPV, and SPC. The performance of the initial design for each scenario is used as the benchmark by which all generated design alternatives are compared.

EXPERIMENT RESULTS & ANALYSIS

Table 1 provides a summary of the recorded data, including the design problem, process and product measurements of each scenario as previously defined. From these results, an improvement in the performance of the generated Pareto solution pool for every scenario can be observed for each design scenario, despite the varying stopping points. In addition, though not included in the data set provided here, it was observed that in each subsequent generation new Pareto solutions were established, resulting in a continuous improvement in the performance of the generated design alternatives. Therefore, it can be confirmed that if time constraints dictate a discontinuing of generated design alternatives that the Pareto solutions of the latest generation will provide improvement over the previous generation. As a result, regardless of the determined stopping point, EEPFD provides a solution pool with improved performance for consideration during the decision making process.

Analysis of the best performance range of each generation's generated solution space revealed that the quantity of improvement over the previous generation decreased rapidly over extended generations eventually converging to zero. As Figure 3 illustrates using scenarios 4, 5 and 8 as examples, the most significant percentage improvement was typically observed in the first 5 generations. This implies that limits on the solution space's potential range may be identified prior to reaching the mathematically convergent criteria which typically requires run times of up to 100 to 1000 generations. This is significant as it begins to suggest a validated interactive influence in early stage design decision-making i.e. designing-in performance as this research conceptually pursues. However, further research is needed to confirm this observation and to negate issues regarding local optimal concerns.

There was also an initial observation that for scenarios with identical design requirements, but varying geometric properties, there was a wide variety in the resulting performance ranges of the solution space. In Figure 4 the 4 scenarios presented possessed identical design requirements, energy parameters, and financial properties. The only varying elements were the geometric properties of the initial design before EEPFD was engaged. As illustrated, there is a significant difference in the resulting performance ranges for each scenario as documented after 6 generations. Further implications of this are discussed in the following section.

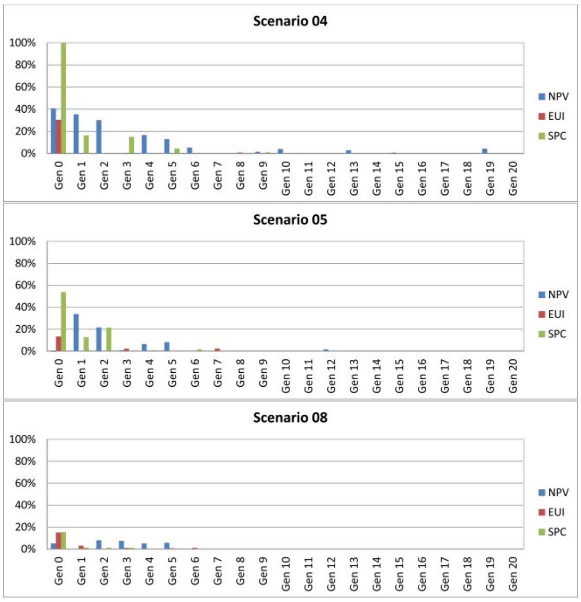

Figure 3 The percentage improvement trend of scenarios 4, 5, 8's solution space range over each generation. Percentage improvement is calculated according to the prior generation.

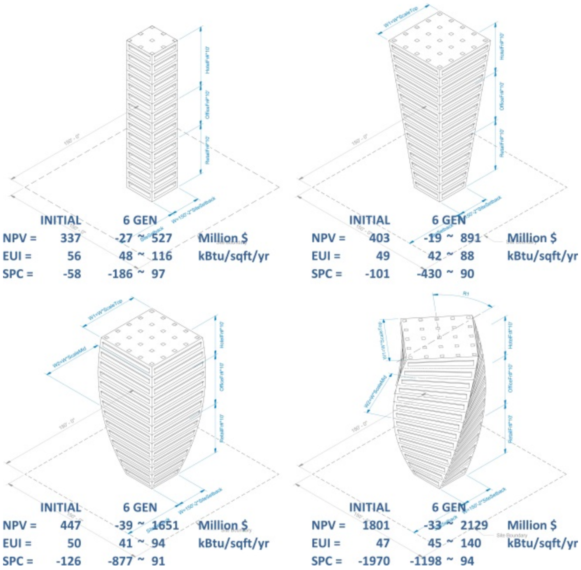

Figure 4 Resulting solution space ranges of four identical design problems but with varying initial parametric designs.

Table 1 Summary of the hypothetical cases measures

Categories/ Measures	Scenario No.											
	1	2	3	4	5	6	7	8	9	10	11	12
Design Problem Measures												
Project complexity												
Project Size (sqft)	167680	84680		167680				16500	31220	51000	3000	86000
Space type no.	4	4	4	4	1	2	4	1	1	3	1	1
Design complexity												
Energy model surface count [i]	794	1587	1042	824	7517	2451	270	1060	28	2086	197	338
Explored parameter # (Design/Energy)	6/61	12/3	16/2	23/3	7/27	8/0	10/3	13/3	0/12	7/4	9/1	6/21
Process Measures												
Speed												
Time spent to run energy analysis (minutes)[ii]	1.46	3.25	2.95	2.96	28.64	8.36	1.01	2.90	0.53	4.15	0.91	1.70
GA Setting												
Initial Population	20	10	10	10	20	10	10	10	40	10	10	20
Crossover Ratio	0.5	0.5	0.5	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6
Mutation Ratio	0	0	0	0	0	0.006	0	0	0.006	0	0	0.006
Population Size	40	30	20	20	40	10	40	20	40	20	20	40
Selection Size	30	30	20	20	30	10	30	20	20	20	20	10
Maximum Iteration	20	6	13	20	1	10	40	20	20	6	5	10
Product Measures												
Feedback quantity												
Feedback number per day (8 hours)	240	34	30	30	5	6	120	80	240	40	240	60
Feedback quality: (Initial/Solutions' range)												
NPV (Million Dollars)	528 155~ 754	71 0~111	150 21~ 247	132 74~52 5	538 142~ 555	(-94) (-516) ~84	738 76~ 741	565 113~ 769	(-73) (-74)~ (-71)	(-41) (-40)~ 834	(-3) (-4)~ (-2)	34 (-57)~ 178
EUI (kBtu/sqft/yr)	55 45~68	56 49~79	55 43~67	62 43~83	65 55~88	57 52-67	48 42~88	61 49~79	56 53~ 104	173 56 ~233	64 51~99	54 47~99
SPC	75 24~94	6 (-4) ~68	3 (-47) ~76	5 5~88	88 38~99	54 (-76)~ 71	31 31~95	83 3~100	100 N/A	10 (-404) ~88	99 46~ 100	99 48~99

Note:

i. The surface count is according to the energy model of the initial design geometry. During the GA process varying design options will have varying surface counts.

ii. These time measurements were according to generating the initial masses' energy models and include the time required to both transfer to and receive results from Green Building Studio through the Internet.

CONCLUSION & DISCUSSION

Through the discussed experimental runs, EEPFD was able to successful demonstrate the ability to adapt to a wide spectrum of design scenarios while providing a solution space with an improved performance as defined by this research for each. Therefore, this research determines that EEPDF can be considered a valid approach eligible for future study. Another subject of interest for future study was identified through an analysis of the performance improvements in the solution space from generation to generation. It can be observed through this data that the optimal performance boundary can be obtained after a few generations of GA runs. After these boundaries have been established the Pareto curve is then more densely populated over the subsequent generations. Through this observation, there is the implication that the performance potential for each design scenario could be identified prior to reaching mathematical convergence. This could result in providing the context in which to gauge any individual solution by the designer in a more rapid manner than otherwise available. In addition, the ability to use these boundaries to gauge the potential of a design alternative may possibly be more relevant to supporting early design decision making than providing the often over populated Pareto defined solution pool.

Another possible application of EEPFD in need of further study stems from observations of distinct needs of early stage design versus other industries or later design phases. When provided identical design requirements and energy parametric settings, but with significantly varying conceptual designs, a wide range in resulting performance boundaries was observed. This implies a direct relationship between the initial conceptual design with its set variations and the resulting performance boundaries outlying the potential performance levels of generated design iterations. While the application of MDO to other fields may be with the intent of optimizing a single design, early conceptual architectural design demands diversity. Therefore, the ability of EEPFD to rapidly determine the performance potential of multiple competing conceptual designs for the same design requirements may be more applicable than pursuing a single optimized solution space. However, the full impact of this observation on EEPFD is in need of further study.

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