MULTIDISCIPLINARY PROCESS INTEGRATION AND DESIGN OPTIMIZATION OF A CLASSROOM BUILDING

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SUMMARY: *Architecture, Engineering, and Construction (AEC) professionals typically generate and analyze very few design alternatives during the conceptual stage of a project. One primary cause is limitations in the processes and software tools used by the AEC industry. The aerospace industry has overcome similar limitations by using Process Integration and Design Optimization (PIDO) software to support Multidisciplinary Design Optimization (MDO), resulting in a significant reduction to design cycle time as well as improved product performance. This paper describes a test application of PIDO to an AEC case study: the MDO of a classroom building for structural and energy performance. We demonstrate how PIDO can enable orders of magnitude improvement in the number of design cycles typically achieved in practice, and assess PIDO's potential to improve AEC MDO processes and products.*

KEYWORDS: *multidisciplinary design optimization, conceptual building design, energy simulation, structural analysis, integration, automation*

1. INTRODUCTION

The advancement of Building Information Modelling (BIM) and analysis methods now allows diverse disciplines to simulate building performance in a virtual environment. The number of performance criteria that

can be analyzed from product models includes architectural, structural, mechanical (energy), acoustical, lighting and an expanding list of other concerns (Fischer 2006). Performance-based design supported by product models is becoming state-of-the-art practice (Hänninen 2006).

However, the potential of this technology to inform design decisions has not yet been fully realized because current tools and processes do not support the rapid generation and evaluation of design alternatives using product models. According to a survey of a leading firm (Flager and Haymaker 2007), it takes architects and engineers over one month to complete a design cycle, which involves generating and analyzing a single design alternative using these methods. During the conceptual design phase, architects and engineers average less than three design cycles per project (Fig. 1, left). The majority of engineers surveyed indicated that they used simulation tools primarily to validate a chosen design alternative, not to explore multiple alternatives. Consequently, AEC professionals often make design decisions with little or no information about the performance of the chosen design compared to alternatives.

AEC professionals' restricted exploration of the design space is the result of a number of tool and process limitations. One limitation is that the vast majority of Computer-Aided Design (CAD) tools used in the industry do not allow the product to be represented parametrically. Parametric representations facilitate the rapid change of geometric and non-geometric variables according to particular design logic (Shah and Mäntylä 1995; Shea, Aish et al. 2005). A second limitation is that these tools do not represent information in a form that facilitates multidisciplinary analysis using simulation-based Computer-Aided Engineering (CAE) tools. Many in the field have written about the inability of the tools used by different disciplines to share data effectively (Gallaher, O'Connor et al. 2004; Wang, Rivard et al. 2005; Holzer, Tengono et al. 2007). As a result of these limitations, the same survey shows that design professionals now are spending less than half of their time doing design and analytic work where they can use their specialized expertise to add the most value to the project. The *majority* of their time now is spent managing design information, including manually integrating and coordinating discipline-specific design and analytical representations (Fig. 1, right).
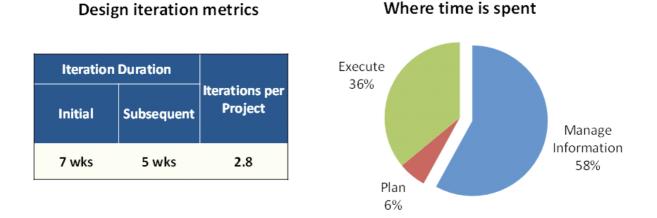

Design iteration metrics

Iteration Duration		Iterations per Project
Initial	**Subsequent**	
7 wks	5 wks	2.8

Where time is spent

Execute 36%

Manage Information 58%

Plan 6%

FIG. 1: AEC professionals only consider a few design alternatives due to significant time spent managing information

Researchers in the aerospace and automotive industries have developed methods for Multidisciplinary Design Optimization (MDO) to address a similar set of limitations in these industries. MDO attempts to formalize problem decomposition and coordination among groups working on the design of complex engineering systems (AIAA 1991). Systematic procedures make it easier to divide work between designers and computers (Vandenbrande, Grandine et al. 2006; Pahl, Beitz et al. 2007); including linking separate CAD/CAE tools to ensure a rapid and accurate flow of data. Potential benefits include compressing design cycle time, enabling designers to consider many more design options and select designs with improved product quality and performance.

MDO methods have been successfully applied in the aerospace and automotive industries (Sobieszczanski-Sobieski and Haftka 1997; Chen and Usman 2001), but their application to AEC practice has been comparatively

modest. Previous research studied Boeing's MDO of a hypersonic vehicle, and speculated that the application of these methods and technology to the AEC industry could prove beneficial (Flager and Haymaker 2007). Boeing's MDO process was supported by Process Integration Design Optimization (PIDO), a class of commercial software commonly used in the aerospace industry to help engineers automate and manage data flow between CAD/CAE tools and to optimize one or more aspects of a product design by iterating across a range of input parameters towards a set of target conditions.

The purpose of this paper is to assess the potential of PIDO tools to facilitate more effective MDO processes in the AEC industry. There are significant differences between AEC and the aerospace and automotive industries in terms of both their organizational structure and the products they produce. The next section of this paper presents a partial list of requirements for applying MDO to AEC projects, and a brief evaluation of relevant existing tools with respect to these requirements. The third section presents a case study that is designed to test the application of PIDO on an AEC project. The case study is a MDO of a classroom building for structural and energy performance. We conclude with an evaluation of the case study results and discuss the potential for using PIDO to support MDO on AEC projects.

2. MDO PROCESS REQUIREMENTS AND EXISTING TOOLS

2.1 Requirements for Multidisciplinary Optimization Processes in AEC

This section lists partial requirements that an MDO method for AEC should meet. We developed the requirements from literature and our own industry experience.

2.1.1 Rapidly Generate Design Alternatives

Researchers argue that the ability to investigate a large number of design alternatives is critical to finding successful designs (Akin 2002). Practitioners must therefore be able to define and modify geometric and non-geometric parameters of a design alternative in a flexible user-friendly environment without significant effort to regenerate geometry and re-assign attributes. Parameterization of design increases complexity of both the design task and the software interface since designers must model not only the artefact being designed, but also a conceptual structure that guides variation. Once design intent has been captured by parametric relationships, however, software automation can significantly reduce the time required for change and reuse (Aish and Woodbury 2005).

2.1.2 Rapidly Analyze Design Alternatives

Once an alternative is generated, practitioners must be able to assess the performance of the alternative across a wide range of criteria in order to make an informed design decision. To manage the large number of alternatives generated, practitioners must be able to automate the analysis of parametrically generated design alternatives. Increased automation frees practitioners from the repetitive task of manually integrating analytical representations, allowing them to spend more time evaluating the results and making design decisions (Pahl, Beitz et al. 2007).

2.1.3 Integrate Conventional CAD/CAE Tools

Practitioners select CAD/CAE tools based on a variety of criteria including capability, performance, usability and cost. In an MDO environment, practitioners need to be able to use tools they trust and with which they are familiar. Therefore, the MDO method should support the effective automation and exchange of information between tools of the practitioner's choice. Such interoperability may occur through either proprietary or open standards-based data models such as Industry Foundation Classes (IAI 2008), or through direct access to Application Programming Interfaces (Myers and Rosson 1992).

2.1.4 Customize Optimization Strategies

The selection of an appropriate optimization strategy depends upon the formulation of the optimization problem, including the objective, constraints, and the number and type (i.e. discrete or continuous) of design variables. A variety of optimization strategies exist to solve different types of problem formulations. For example, formal methods such as mathematical programming (Fleury and Braibant 1986) and optimality criteria (Berke and Khot 1987) generally perform well when the problem can be assumed to be continuous, while heuristic methods such as evolutionary algorithms (EAs) (Deb 1999; Machwe, Parmee et al. 2005; Parmee, Abraham et al. 2008) tend to

be superior when applied to problems with non-linear, stochastic, or chaotic components. Practitioners therefore need to customize optimization strategies based on the particular requirements of the design problem.

2.1.5 Visualize Trade Spaces

Applying computational optimization methods to conceptual design has proven difficult because a problem typically has multiple objectives and is imprecise with respect to one or more of these objectives (Shaw, Miles et al. 2008). In addition, design objectives and constraints often change during the design process based on observations and interpretations of results (Gero and Kannengiesser 2004). The interaction of human expertise and computer-based exploration therefore is essential for the process to be successful. Designers need to be able to understand general performance trends as well as variable sensitivities in order to make informed decisions in guiding the optimization process. Advanced plotting tools that enable multi-dimensional data visualization such as Pareto (Grierson and Khajehpour 2002; Khajehpour and Grierson 2003; Stump, Yukish et al. 2004) and Parallel Coordinate (Parmee 2005; Parmee, Abraham et al. 2008) plots have proven useful for this purpose.

2.1.6 Communicate Process and Information Dependencies

Practitioners must be able to understand the steps involved in the MDO process easily, as well as how information flows between process tasks. This is important for quality control purposes (Baldock, Shea et al. 2005) as well as to improve the reusability of the process on future projects (Lee, Sacks et al. 2007), since it may involve the modification of the original process by new personnel. Researchers have developed methods to visually communicate process and information dependencies, e.g. (Steward 1981; Smith and Eppinger 1997; Haymaker, Kunz et al. 2004).

2.2 Strengths and Limitations of Existing Tools in Meeting the MDO Requirements

This section briefly discusses several design optimization techniques/tools in the context of the AEC requirements outlined in the previous section.

2.2.1 Computing Platforms for Structural Optimization

The first application of computational optimization methods to structural design followed the development of reliable Finite Element Analysis (FEA) methods in the 1950s and 1960s. Subsequently, researchers have focused on (1) developing algorithms capable of dealing with a variety of different types of optimization formulations, (2) formulating decision-making methods for problems with multiple objectives, and (3) integrating conventional CAD/CAE software into the optimization process.

Developing robust and efficient optimization algorithms to deal with structural topology, shape and member sizing has been the focus of a large body of work. Researchers have experimented with evolutionary computing methods, including genetic algorithms (Grierson and Pak 1993; Deb and Gulati 2001; Togan and Daloglu 2008), genetic programming (Soh and Yang 2000; Baldock and Shea 2006; Giger and Ermanni 2006; Hasançebi 2008) and simulated annealing (Kirkpatrick, Gelatt et al. 1983) to sample and find areas of good performance in highly complex, multi-dimensional search spaces. This research has enabled designers to optimize fairly large, complex problems, including electric transmission towers (Shea and Smith 2006) and bracing topologies for tall building structures (Baldock, Shea et al. 2005). However, these methods have not supported multi-objective optimization, nor do they adequately visualize the optimization process and results.

Optimization methods that are able to manage multiple, conflicting objectives has been an active field of research in recent years. Khajepour and Grierson have developed methods involving multi-objective genetic algorithms (MOGAs) and Pareto optimization to investigate trade-offs for high-rise structures (Grierson and Khajehpour 2002; Khajehpour and Grierson 2003). Grierson subsequently has developed a Multi-Criteria Decision Making (MCDM) strategy that employs a trade-off analytic technique to identify compromise designs in which competing criteria are mutually satisfied in a Pareto-optimal sense (Grierson 2006; Grierson 2008). In related work, Parmee and Machwe have led efforts to incorporate aesthetic criteria into the decision-making process through the use of interactive methods and machine learning that incorporate designer preferences into the computational optimization process (Machwe, Parmee et al. 2005; Machwe and Parmee 2007). The methods, however, are not integrated with conventional CAD / CAE tools nor can they incorporate parameters that lie outside of the structural design domain.

Related research has created integrated, performance-driven, generative design tools that link CAD, FEA and optimization software. To guide this generative method, Shea et al incorporated an optimization process called Structural Topology and Shape Annealing (STSA), which combines structural grammars; performance evaluation, including structural analysis and performance metrics; and stochastic optimization via simulated

annealing (Shea, Aish et al. 2005). Similarly, Holzer et al used a parametric CAD tool linked with a proprietary optimization algorithm to optimize the shape of a stadium roof structure (Holzer, Hough et al. 2007). This work has shown that software integration can lead to improved collaboration among multiple disciplines (i.e. architects and structural engineers) and to better performing designs. However, these systems do not provide capabilities to adequately visualize multi-dimensional design spaces or to decide between competing objectives.

2.2.2 Computing Platforms for Energy Optimization

Government and academic researchers have developed a variety of optimization platforms for energy performance. National Renewable Energy Laboratory (NREL) developed BEopt and OptEPlus. BEopt uses the DOE2 and TRNSYS simulation engines and a sequential search technique to optimize building designs (Christenson, Anderson et al. 2006). The application includes a Graphical User Interface (GUI) that allows the user to select from a range of predefined and discrete building alternatives to be used in the optimization process. BEopt allows the user to rapidly generate and visualize the design space through a browser, but its flexibility is limited as a result of having predefined building alternatives and its inability to consider a wide range of objective functions. OptEPlus utilizes EnergyPlus and various search routines to identify optimal buildings designs for energy usage (Ellis, Griffith et al. 2006). The framework consists of a collection of EnergyPlus input and output files, system directories, and computer routines that use an XML data model to transfer information among the various components. This application integrates with multiple data sources, is modular to allow distributed programming, and supports selection of automation and optimization strategies. Visualization of the trade space however is limited, and it does not support multidisciplinary optimization.

Recently, Evolutionary computing (EC) has been explored in energy performance analysis (Wright, Loosemore et al. 2002; Fong, Hanby et al. 2006). GENE_ARCH combines the use of a Genetic Algorithm (GA) and DOE-2 for constraint-based, multi-objective optimization (Caldas 2006). The application has advanced geometry generation functionality, is scalable, and has good visualization capabilities. GENE_ARCH, however, does not allow for multi-disciplinary optimization using multiple simulation engines. GenOpt is a generic optimization program that can be used with any simulation program that has text-based input and output, such as EnergyPlus, DOE-2, SPARK, BLAST, TRNSYS, or any user-written code (Wetter 2000). This tool is able to access a library of different optimization algorithms, and can use either continuous or discrete variables. The modularity, flexibility, and ability to select from a range of optimization strategies make GenOpt a robust platform, but its visualization capabilities are limited.

2.3 PIDO Software Framework

Process Integration and Design Optimization (PIDO) comprise software and design techniques intended to help engineers and analysts (Daratech 2001):

- Automate and manage the setup and execution of digital prototyping, simulation, and analysis tools

- Integrate and/or coordinate analysis results from multiple physical domains in order to produce a more holistic model of product performance

- Optimize one or more aspects of a product design by iterating analyses of the design across a range of input parameters toward a specified set of target conditions.

After evaluating commercially available PIDO software against the requirements listed in Section 2.1, we selected Phoenix Integration's ModelCenter® to implement the case study. ModelCenter allows users bring commercial or proprietary software tools into a common environment using a software "wrapper" or "plug-in" which interfaces with the tool to be automated. Once an integrated model has been built, ModelCenter's design exploration and optimization tools can be used to perform optimization and trade-off studies, and to compare different design options.

The next section describes a case study application of ModelCenter to support MDO on a classroom building. We use this case study to assess the extent to which an MDO process implemented in ModelCenter can satisfy the requirements of the AEC industry as defined above.

3. CASE STUDY

3.1 Overview

The case study we chose to evaluate was a single room classroom building, with windows on two opposite facades and a steel frame structure (Fig. 2, left). We evaluated the classroom design for its structural integrity, energy consumption, daylighting as well as initial capital and life-cycle costs. We chose San Diego, CA as the building's location for the purpose of determining weather conditions, building regulations and energy costs.

The objectives for the case study were to:

- Minimize the capital cost of the building's steel frame
- Minimize the life-cycle cost for the building's operation

The design constraints were:

- Structural safety: All the members of the steel frame had to meet building code requirements for strength (Code 1997).
- Daylighting performance: Maximum annual average lighting power multiplier of 0.6.
- Space: Floor area fixed at 960 sq ft, and the single-story height fixed at 10 feet.

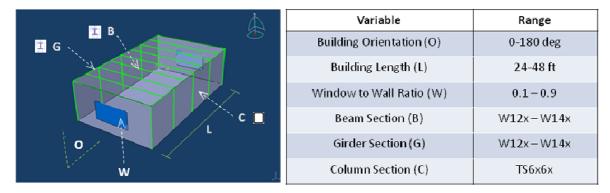The design variables for the study are shown in Fig. 2, right.

Variable	Range
Building Orientation (O)	0-180 deg
Building Length (L)	24-48 ft
Window to Wall Ratio (W)	0.1 – 0.9
Beam Section (B)	W12x – W14x
Girder Section (G)	W12x – W14x
Column Section (C)	TS6x6x

FIG. 2: Design variables for classroom case study

Next, we discuss the design process, optimization, and results in three parts: structural, energy, and combined structure and energy.

3.2 Structural Design Process, Optimization, and Results

The structural optimization process model for the classroom case study is shown in Figure 3 below. The model representation is based on the Design Structure Matrix (DSM) (Steward 1981) and Narratives (Haymaker, Kunz et al. 2004; Haymaker 2006). The five major components are represented along the downward diagonal of the diagram, going from left to right. In DSM, horizontal arcs represent the outputs from tasks, while vertical arcs represent inputs to the tasks. The coupling between modules is represented by a solid circle. Couplings above the diagonal of the DSM are feed-forward couplings, representing sequential execution. Couplings below the diagonal of the DSM are feedback couplings, representing iteration.

The major components in the process are described in more detail below, along with the optimization formulation and results.
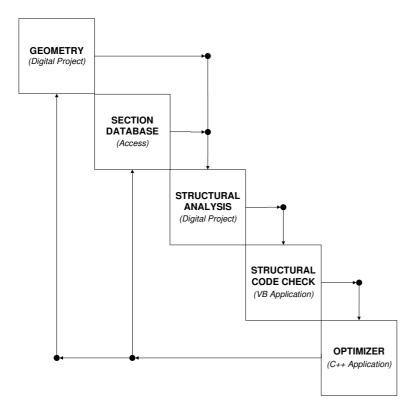
FIG. 3: Structural design, analysis, and optimization process

3.2.1 Geometric Design

The geometry for the classroom building was created using the parametric CAD software Digital Project (DP 2008), and is shown in Fig 2, left. The structural analysis representation consisted of centreline geometry for all of the structural members in the model. There were 9 beams spanning the roof, and 8 girders transferring the load to 10 supporting columns. The independent variable in the structural geometry model is building length. One of the challenges associated with the structural model was that varying the geometry of the building changed the loading on the structural members. To ensure that the loading remained accurate for all possible geometric configurations, parametric loading panels were defined for each structural member in the model. The area of these panels corresponded to the tributary area of the building that each member was responsible for supporting. The area of each panel updates automatically when the building geometry changes. The point coordinates defining the structural members and the loading panels are automatically loaded into the structural analysis software.

3.2.2 Structural analysis

The Finite Element Analysis (FEA) for the structure was performed using GSA (GSA 2008). Once the centreline geometry for the structural members is imported into GSA, all of the structural properties for the members including steel sections, member end conditions, and loading are defined manually in GSA. We considered three load cases in the analysis: (1) dead load, consisting of the weight of the structure, (2) live load, consisting of the weight of occupants and impermanent furniture, equipment etc., and (3) wind loads for the site. We then combined these loads into five-factored load combinations as specified by the building code. Once all of this information was specified in GSA, the FEA was run and internal forces and moments for each member were exported by load combination to the code check component along with selected member properties. For each subsequent iteration, the point coordinates defining the structural members and the loading panels were updated automatically.

3.2.3 Structural code check and cost calculator

The structural code check and cost calculator is a custom Visual Basic application. The code check component determines if the structural members have sufficient strength to resist the applied loading as specified by the building code (Code 1997). This is determined by calculating the factor of safety (FS) for each member under each load combination, where: FS = demand (D) / capacity (C). The demand (D) is calculated based on the

applied forces and moments from the structural analysis. The capacity (C) is calculated based on applied loading and the member properties. A FS of less than unity indicates that a particular member meets all of the structural design requirements for strength. A constraint in the optimization process was to have the FS for all members be less than one. This was expressed as a single constraint in the formulation of the optimization problem (max (FS) < 1). The cost calculator component calculated the total cost of the building's steel frame based on the sum of the weight of each member multiplied by an assumed price of steel per unit weight.

3.2.4 Structural optimization

Our preliminary investigation of the design space indicated that it was highly non-linear; meaning small changes in variable values sometimes resulted in large changes in performance. This observation, combined with the optimization formulation being comprised of only discrete variables, led us to choose a genetic algorithm to perform the structural steel optimization study. Genetic algorithms utilize processes analogous to natural selection to stochastically search for the best designs. Since they do not require objective or constraint gradient information, genetic algorithms are able to search discontinuous and "noisy" design spaces effectively. Compared to gradient-based optimization algorithms, we concluded genetic optimizers are much more likely to find globally optimal designs for this problem.

We configured the optimization problem in ModelCenter's genetic algorithm-based optimization tool called Darwin (Darwin 2004). The size of the design space for a section optimization study consisted of approximately 29,575 possible designs. In order to optimize for structural geometry, a section optimization was conducted for each geometric configuration. We looked at four different building lengths: 24ft, 32ft, 40ft, and 48ft. The following genetic algorithm parameters were used for the optimization run: Population Size = 25; Probability of Crossover = 100%; Probability of Mutation = 5%; Convergence Criteria: Fixed number of iterations = 250.

3.2.5 Results

Our objective in the structural optimization process was to minimize the cost of the steel frame while satisfying structural safety criteria for strength design. The genetic algorithm described above converged in approximately 300 iterations (1% of the total possible designs). A single iteration took approximately 10 seconds running on desktop PC with a 3.00GHz processor and 8GB of memory.

The scatter plot (Fig. 4) shows the results of the section optimization for beams in the structure. Each design candidate (consisting of a unique set of steel section sizes) is represented as a single point. The best performing designs (i.e. cheapest designs that satisfy the constraints) are dark blue. Grey points represent infeasible designs (i.e. those which do not satisfy the structural strength criteria). The two different swaths of design points shown in the plot correspond to the two different depths of beam section that were considered in the optimization (W12x and W14x). From the graph, one can quickly see the most efficient section sizes for the given problem as well as the trade off between different section sizes and depths.
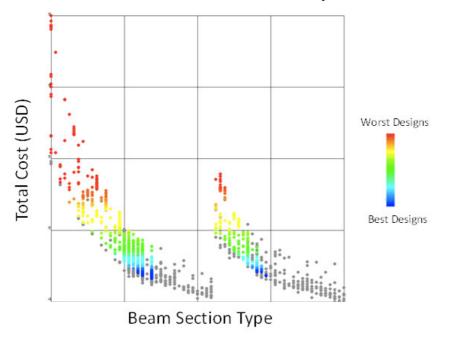

FIG. 4: Beam section optimization results

The parallel coordinates plot (Fig. 5) provides an alternative view of the design space. The ranges of values for each variable are represented as a vertical axis (increasing in value from the bottom of the axis to the top). Each coloured line represents a different design. As in the scatter plot, the darker blue lines represent the best designs. The point where each line intersects a vertical axis represents the value of the corresponding design variable for a particular design. Visualizing results in this fashion allows the designer to quickly identify the range of variable values that often result in the best design configurations. For example, we can see that the best designs all have a small range of beams section sizes in the two depths considered (as shown in the scatter plot). The best (blue) designs also pass through the entire range of column sections, indicating that the choice for column size from the available alternatives has less influence on design performance.

The parallel coordinates plot also shows that designs which have a larger building length (see Fig. 2) perform better. This is what we might expect based on structural engineering principles given that roof beams are simply supported and governed by gravity loading. As the building length increases, the loading (w) increases, but the beam span (S) is reduced due to the floor area constraint described in the overview. Therefore, as expected, the maximum bending moment decreases as the building gets longer, allowing for lighter beam sections and a cheaper overall design.
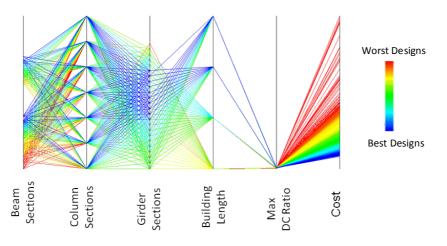

FIG. 5: Impact of structural design variables on building steel cost

3.3 Energy Design Process, Optimization, and Results

This section describes the energy design process including geometric design, analysis, optimization, and results. The process is shown in Fig. 6.
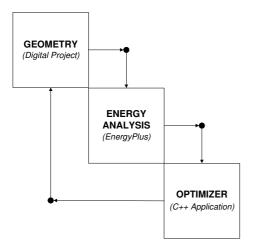

FIG. 6: Energy design, analysis, and optimization process

3.3.1 Geometric Design

The geometry was generated using the same Digital Project model described in section 3.2.1. The design space was constrained to be a rectangular room with two windows on the grid east and west walls. The independent variables were building orientation, building length, and window-to-wall ratio (See Fig. 2). The windows were centred on their respective walls and the aspect ratio of the windows was constrained to be the same as the wall. A daylighting sensor location point was placed in the centre of the room two feet above the ground level. Wall, roof, and floors were modelled as single planar surfaces. Four node coordinates for each wall and window surface, and the daylighting sensor were then passed onto the energy analysis component.

3.3.2 Energy analysis

The thermal performance of the classroom was analyzed using EnergyPlus. The thermal runs simulated the energy requirements to maintain a space temperature of 70-73°F between 7am-4pm Monday-Friday (operation hours for the classroom) with setbacks of 50°F and 90°F for off operation hours during the winter and summer, respectively. The building was assumed to operate all year, except holidays. The HVAC system used was a Packaged Terminal Air Conditioner (PTAC) with gas heating and electric cooling. The lighting load was set at 1.5 watts/ft^2, the equipment load at 1.0 watts/ft^2, and the number of occupants for the classroom was 20. The wall/roof construction had a structural steel frame with rigid board insulation and the floor was an un-insulated concrete slab. The windows were modelled as argon filled double pane and low-e.

For the process to be automated, the EnergyPlus input file had to be parametric to absorb changes to the building node coordinates and the daylighting sensor location. This was done using a batch file format that gathered together the input data and modified the EnergyPlus input file to conduct the runs.

The outputs from EnergyPlus consisted of the annual energy intensity, cooling energy intensity, heating energy intensity, lighting energy intensity, solar heat gain intensity, and annual operating costs for gas and electricity. The unit cost for gas and electricity were based on local utility rates. Total life-cycle operating costs were calculated over a lifetime of 30 years in current dollars using a 3% discount rate. The EnergyPlus simulation also provided us with values for the hourly lighting power multiplier for the building, which was averaged over the total number of operational hours during the year to provide a single representative annual average lighting power multiplier for the design. The lighting power multiplier is the fraction of artificial lighting that is required to meet the design luminance in the space. A lighting power multiplier of 0 means the space is completely day lit and 1 being completely lit by artificial lights.

3.3.3 Energy optimization

A Design of Experiments (DoE) was conducted to evaluate performance trends over the entire spectrum of the design space. The DoE tool in ModelCenter was used to gather information about the analysis model's behavior by running it for a number of different input variable combinations. The DoE tool is a convenient way to begin exploring the design space, and is often the starting point used to validate more sophisticated model methods like optimization. N-dimensional parametric studies can be performed by specifying the number of samples for each of the input variables or you can choose from a variety of pre-defined "experimental designs", including Full Factorial, Central Composite, Latin Hypercube, or a customized experiment. In this case, a customized factorial was used involving the evaluation of 1881 different designs.

We chose to compare the results of the DoE with the results of the optimization to evaluate differences in the two methods in terms of performance of the 'best' design and the required simulation time. A gradient-based algorithm was selected to perform the optimization study because the optimization formulation comprised a single objective and continuous design variables. The algorithm chosen was called Design Explorer (DesignExplorer 2004), which was developed by Boeing to solve complex problems characterized by long running models, noisy search spaces, and multiple optima. It intelligently uses non-physics based mathematical models to reduce the number of required model executions. It is a global search algorithm, so it is not likely to get stuck in local optima.

The design variables were building length, window-to-wall ratio, and orientation (Figure 2, right). The performance constraint was the annual average lighting power multiplier. We set the single objective function to minimize total life-cycle operating costs.

3.3.4 Results

We explored the data generated by the Design of Experiments (DoE) including surface charts to understand general trends and glyphs charts to study data point spreads. In our particular case study, the tradeoffs between daylighting performance and energy performance were evaluated by varying window size, building length, and orientation. Larger windows generally result in improved daylight in the space, a reduction in artificial lighting (assuming photo sensors and dimmable ballasts for the lighting), and a consequent reduction in ventilation and air-conditioning energy consumption due to the reduced heat load from the lighting energy. However, the larger windows also result in larger solar heat gains to the space and conductive losses through the fenestration, which increase the load on the HVAC system. In addition, changes to the relative total window to wall area of the building changes the relative envelope conductive heat gains/losses.
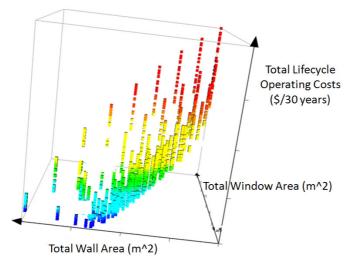

FIG. 7: Glyph chart of building window and wall area vs. lifecycle operating cost

The glyph chart in Fig. 7 shows that the designs with the lowest total life-cycle energy costs are those with the highest total wall area and the lowest total window area. Each point represents a design alternative, with blue representing the best and red the worst performing designs. Intuition would suggest that total energy consumption would be minimized when both window area and wall area are minimized; however the chart shows that due to the geometric constraints, a design that minimizes total window area cannot result in a total wall area in the lower range of that parameter. This is an example of how data visualization capabilities in ModelCenter can allow a designer to interpret what may otherwise may be a complex and non-transparent solution space, in this case why architectural constraints prevent energy consumption from reaching the lowest possible value for the given floor area.
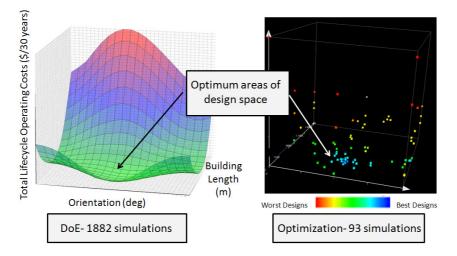

FIG. 8: DoE results vs. optimization results. Both plots show building orientation and length vs. lifecycle operating cost.
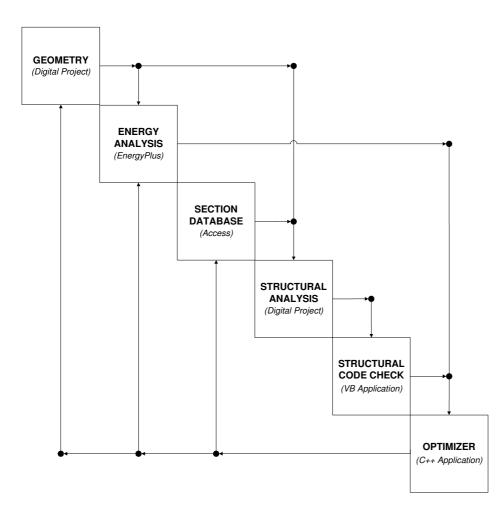
Figure 8 compares the results of the DoE with the optimization. The correlation between the optimum designs using DoE and the optimizer was extremely high, with the optimizer identifying the best performing design with almost the exact same design characteristics as the best design identified in the DoE. The daylighting performance constraint applied in the optimization resulted in little variation in optimum designs since the vast majority of the designs had annual average lighting power multipliers less than 0.6 due to the shallow range of building depths relative to the range of window areas present in the design space. The number of simulations required to achieve the optimum design was reduced from 1881 to 93 (95%).

3.4 Multidisciplinary Optimization and Results

The following section describes the combined structural and energy MDO formulation and the results.

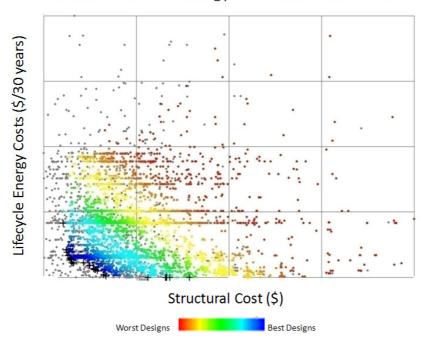### 3.4.1 Multidisciplinary Optimization

The multidisciplinary geometric design and analysis inherited the characteristics and parameters of the structural and energy analyses. The fact that the optimization formulation was comprised of both continuous and discrete variables and multiple objectives led us to choose Darwin (Darwin 2004) to perform the multidisciplinary optimization study. For multi-objective problems, Darwin will generate Pareto trade-off curves, with the points on the curve all being optimal in the sense that each represents a design point at which it would be impossible to improve one of the objectives without degrading the other(s). The objective functions, constraints, and design variables used for the combined optimization were the same ones listed in Fig. 2. Building orientation was varied from 0-180 degrees (in 10 degree increments), the building length varied from 4-14 meters (in 1m increments), and window-to-wall ratio from 0.1-0.9 (in 0.1 increments). For the structural analysis, there were 65 types of girders, 7 types of columns, and 65 types of beams. The design space had a population of approximately 55×10^6 possible designs. The following genetic algorithm parameters were used for the optimization run: Population Size = 25; Probability of Crossover = 100%; Probability of Mutation = 5%; Convergence Criteria: Fixed number of iterations = 250. The MDO process is shown in Fig. 9.

FIG. 9: Multidisciplinary design, analysis, and optimization process

3.4.2 Results

The optimization run required 5,600 iterations (0.01% of the total number of possible designs). This took approximately 34 hours on a desktop PC with a 3.00GHz processor and 8GB of memory.

The trade-off between structural costs and energy (operating) costs is shown in Fig. 10. The designs marked with a black '**+**' are Pareto optimal. One can see that the best designs from the perspective of operating cost have a relatively high capital cost and vice versa. The 'optimal' design depends on the client's preference. Only by analyzing and visualizing a large number of design alternatives is it possible to accurately characterize these tradeoffs. For example, Fig. 11 illustrates how building length impacts the first and life-cycle costs of the classroom. The cost of the structure decreases as the length of the building increases because as the length of the building increases, the beam span is reduced, resulting in a more efficient (and cheaper) structural frame. From the perspective of operating costs, however, the building becomes less efficient as the building length increases. This is due to several factors, including greater surface area of building skin, which resulted in greater conductive losses, and a larger wall area for windows to meet day lighting requirements, which resulted in increased solar gains and cooling requirements. These figures are examples of how designers can use PIDO to better understand performance trade-offs, allowing them to make more informed decisions.

Structural Cost vs. Energy Cost with Pareto Front

FIG. 10: Pareto front showing the trade-off between minimizing life-cycle energy costs and structural first costs
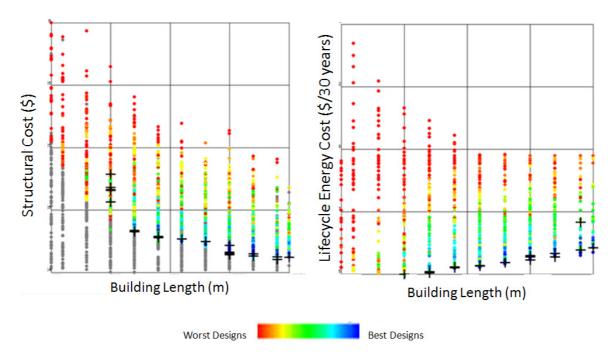
Fig. 11: When structural costs (left) and energy costs (right) are plotted against building length, the Pareto optimal designs show opposite performance trends

4. CONCLUSIONS AND FURTHER WORK

AEC practitioners today typically create very few design alternatives before choosing a final design. Design theory argues that this leads to underperforming designs. The aerospace and automotive industries have overcome similar limitations using MDO methods implemented in PIDO software, resulting in reduced design cycle time and improved product performance. For the AEC case study presented, we found that PIDO software enabled orders of magnitude improvements in the number of design cycles when compared to conventional methods. Instead of the usual two to three design cycles in a typical project, using PIDO we were able rapidly to analyze over 5,000 design alternatives and choose from a range of near-optimal solutions. We now discuss our observations with respect to the MDO requirements we outlined in section 2.1.

4.1 MDO Process Requirements and PIDO Case Study Application

4.1.1 Rapidly Generate and Analyze Design Alternatives

Alternatives were automatically and rapidly generated using the parametric CAD model. The challenge was in creating and integrating the geometry for the analysis representation into a common parametric logic. This step required close coordination among the design team members and thorough testing to ensure that the analysis representations were valid over the full range of design parameters. Once a robust parametric model was developed, ModelCenter successfully automated the creation of analytical representations for structure and energy. In this case study, the space of alternatives we explored was limited because the classroom was geometrically simple and topological variations were not explored. Future work should test alternative topology generation techniques in the PIDO environment.

Due to the simplified nature of our case study, simulation times for both structural and energy performance were minimal. Even with minimal simulation times and a limited number of design variables, our MDO of 5,600 alternatives took 34 hours. Practitioners typically work on larger, more complex projects with much larger design spaces. On projects of this scale, the computation time required for MDO may be a major barrier. This obstacle, however, may be addressed with the utilization of distributed and parallel computing and improved analysis application performance and wrapper communication.

4.1.2 Integrate Conventional CAD/CAE Tools

ModelCenter was able to integrate and automate the industrial applications we selected. The only requirement was that the application be able to run in batch mode. We needed software development expertise to write the wrappers, an uncommon skill among architects and civil engineers. Once wrappers have been written, however,

engineers and architects can reuse wrappers to create new processes as long as the data inputs and outputs are supported. On this project, it took approximately 100 man-hours to integrate EnergyPlus, 200 man-hours to integrate GSA, and 60 man-hours to write the structural code checker. CATIA/Digital Project already had a plug-in available. We believe this development work can be reused on future projects, but more work is needed to test the generality of the wrappers. There are many other AEC tools including lighting and computational fluid dynamics (CFD) analyses which are not currently wrapped for the ModelCenter Environment. Future work should implement these wrappers and test their suitability for inclusion into the PIDO methodology.

We avoided typical interoperability issues frequently encountered in integrating industry CAD and CAE applications by bypassing the intermediate step of converting geometric information into a proprietary or open-data schema and then importing and converting that information into the receiving application's required format (Eastman, Wang et al. 2005). Future work should test the viability of utilizing emerging industry standard data models for information exchange such as IFC, and to measure and compare the development and execution time necessary to automate the process against the benefits gained.

4.1.3 Customize Optimization Strategies

Once automated, we were able to choose from a variety of optimization methods suitable for both discrete and continuous variables. In this project, we used a genetic algorithm for the discrete structural section optimization analysis and a gradient-based method for the energy optimization analysis. A genetic algorithm was used for the multidisciplinary optimization. The optimization methods worked well for these respective formulations. Further research is needed to examine whether these optimization methods are capable of tackling larger, more complex AEC design problems or whether new methods will be required.

4.1.4 Visualize Trade Spaces

We used advanced tools for multi-dimensional visualization, including glyph, parallel coordinates, scatter, and histogram plots. The visualizations may be represented with any combination of input design variables and output results. This allowed us to understand general performance trends as well as variable sensitivities to support the decision-making process. For example, the parallel coordinates plot in Fig. 5 revealed that the choice of column section was not as influential as the choice of beams. In the energy design process, the Design of Experiments tool allowed us to visualize the entire design space and to validate the optimization method (Fig. 8). Future work is needed to allow designers to explore the design space and simultaneously see the impact upon product performance and geometry.

4.1.5 Communicate Process and Information Dependencies

ModelCenter contains a window for viewing the process similar to the process diagrams shown (Fig. 3, 6 and 9). It is possible to further interrogate this model to determine data dependencies. We found it helpful to sketch the process before implementation in ModelCenter in order to identify the actors responsible for each step in the process and the specific information being exchanged. These diagrams helped us communicate the processes, and to plan interoperability strategies. Future work should include the integration of such visualizations of process and data interoperability into the PIDO software and the testing of the extent to which they aid design teams design and manage MDO processes more easily.

In conclusion, we found that PIDO has great promise to transform the AEC industry by changing the way we solve design problems; by giving us the ability to generate and analyze many times the number of design alternatives; and by providing tools and methods to systematically search for better performing building designs. The work on PIDO, nevertheless, is in its early stages, and much work remains to determine the applicability of PIDO on large scale, complex AEC projects and how it may be integrated with conventional tools and methods.

5. ACKNOWLEDGEMENTS

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