CIFE CENTER FOR INTEGRATED FACILITY ENGINEERING

Multidisciplinary Process Integration & Design Optimization of a Classroom Building

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ABSTRACT: *Architecture, Engineering, and Construction (AEC) professionals typically achieve very few design and analysis iterations 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 using a technique known as Process Integration and Design Optimization (PIDO), resulting in a greater number of design iterations and improved processes and product performance. This paper describes a test application of PIDO to an AEC case study: the multidisciplinary design and optimization (MDO) of a classroom building for structural and energy performance. We demonstrate how PIDO can enable orders of magnitude improvement in the number of iterations typically achieved in practice, and assess the methodology's potential to improve AEC MDO processes and products.*

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

1. INTRODUCTION

The advancement of computer-based product modeling or Building Information Modeling (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). Consequently, performance-based design supported by product models is becoming state-of-the-art practice (Hänninen, 2006).

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. According to a survey of a leading firm (Flager, 2007), it takes architects and engineers over one month to generate and analyze a design option using product models. Due to the limited time available in conceptual design, this means, each project typically achieves less than three such iterations (Fig. 1). The majority of engineers surveyed indicated that they used model-based methods primarily to validate a chosen design option rather than to explore multiple alternatives.

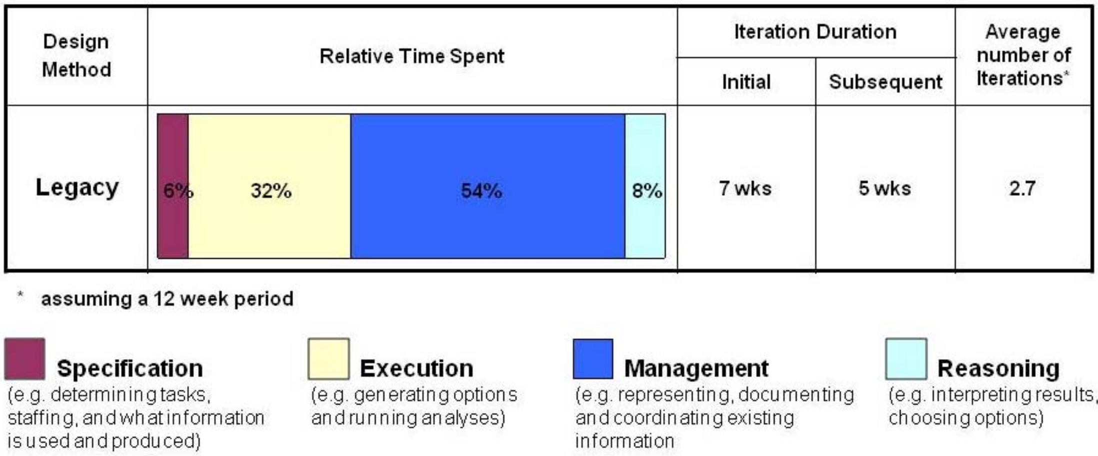


FIG. 1: Building Design Process Metrics (Flager, 2007)

This narrow formal investigation of the design space in current practice results from a number of tool and process limitations. One limitation is that designers' tools are intended to generate static design options, rather than help define and explore solution spaces. Another limitation is that when information is produced, little consideration is given on how to represent that information to facilitate multidisciplinary analysis. Many have written about the inability of tools used by different disciplines to share data effectively, which is necessary for effective multidisciplinary analysis (Gallaher, 2004). The survey shows that as a result of these limitations, design professionals are now spending less than half of their time doing 'value-added' design and analysis work. The majority of their time is spent managing design information, including manually integrating and coordinating discipline-specific design and analysis representations. These limitations prevent a more thorough and systematic exploration of the design space based on multidisciplinary model-based performance analysis.

In contrast, by adopting a suite of new technologies and methodologies that support multidisciplinary design, analysis and optimization (MDO), the aerospace industry has overcome many of these limitations. Product models for parametric geometry definition, integrated design schemas, automated discipline analysis, and multidisciplinary optimization have been developed to improve process and product performance (Bowcutt, 2004). These methods have been integrated into a suite of new tools that can help facilitate Process Integration and Design Optimization (PIDO). Previous research studied Boeing's Multi-Disciplinary Design and Optimization (MDO) process that was used for the design of a hypersonic vehicle, and speculated that the application of these methods and technology to the AEC design process (Flager, 2007) could prove beneficial.

There are significant differences between the AEC and aerospace industries in terms of both their organizational structure and the products they produce. The next section of this paper presents a partial list of process requirements for applying MDO to an AEC project derived from theory and industry experience, a brief evaluation of relevant existing tools with respect to these requirements, and an introduction to the PIDO platform.

The third section presents a case study that is designed to test the application of these methods and technologies to an AEC project. Its purpose is to determine the potential of PIDO technologies and methods to improve the AEC design process through a more thorough and rapid exploration of a design space. Although "optimization" typically implies a mathematical exploration of a design space and in the broadest sense can include manual calculations (Frank, 1992), we use the term in this paper to refer to design space exploration which relies on automation to produce systematic rules-based iterations.

The case study consists of the multidisciplinary optimization of the structural and energy performance of a classroom building. First, we present an overview of the case study project. Next, we describe the process and results of the analysis and optimization process. The structural discipline is presented first followed by energy and then the combined optimization of both structure and energy together. We conclude with an evaluation of the case study results and the application of PIDO to the AEC industry. This is followed by a brief discussion of future PIDO development efforts for AEC projects.

2. MDO PROCESS REQUIREMENTS AND EXISTING TOOLS

2.1 Requirements for Multidisciplinary Optimization Processes in AEC

This section lists partial requirements that a multidisciplinary optimization methodology for AEC should meet. We developed the requirements from literature and our own industry experience.

2.1.1 Integrate Conventional CAD/CAE Tools

Practitioners need to be able to use tools they trust and are familiar with. The method used must support the effective exchange of information between these tools. Such interoperability may occur through either proprietary or open standards-based data models (ISO, 2003), or through direct access to application programming interfaces (APIs) (Myers and Rosson, 1992).

2.1.2 Rapidly Generate and Analyze Alternatives

Practitioners must be able to generate and modify geometrical and non-geometrical models in a flexible environment without significant effort to regenerate geometry and re-assign attributes. Researchers argue that the ability to investigate a large number of alternatives is critical to finding successful designs (Akin, 2001).

Once options are generated, practitioners need to quickly assess the performance across a wide range of criteria. Interoperability enabled by the requirement discussed in section 2.1.1 assures an effective transfer of design to analysis representation. Practitioners, however, must be able to use tools that automate the exchange of information between applications in order to to manage the large number of alternatives generated for the requirement in section 2.1.2. Furthermore, increased automation frees practitioners from repetitive manipulation allowing them to spend more time generating and evaluating design alternatives (Balzer et al, 1983).

2.1.3 Apply Multidisciplinary Optimization Strategies

To accommodate the analysis of a large number of design alternatives and reduce the number of times expensive simulation codes must be executed, practitioners must be able to explore the design space systematically, using one or more optimization strategies. Other forms of systems to support conceptual design have been proposed (e.g. Mora et al., 2006), but without a search engine to guide the designer through the large number of options generated, designers would have difficulty finding the best performing designs other than by chance. The robustness of the optimization process is a function of the ability to choose from multiple algorithms to meet the specific characteristics of the design problem. These strategies may include gradient, genetic, and other types of optimization strategies that can accommodate discrete and/or continuous design variables. Generally, continuous design variable optimization strategies, such as gradient-based strategies,are not well suited to the AEC industry, where the options analyzed frequently consist of discrete options such as a section type for structural analysis or a construction type for thermal analysis (Ellis et al., 2006) (Wetter and Wright, 2003). With an increasing emphasis being put in integrated design (AIA, 2007), a robust methodology for building performance optimization should enable employing optimization strategies across multiple disciplines.

2.1.4 Visualize Trade Space

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. Furthermore, the objectives and constraints, on which the search for solutions is based, often change during the design process (Shaw et. al. 2008). The search process also is interactive, with decisions being made based on observations and interpretations of results, which are derived in an iterative fashion (Kannengiesser and Gero, 2004). The interaction of human expertise and computer-based exploration therefore is essential for the process to be successful. This requires clear communication of search results in a form which other disciplines can understand and which thereby encourages creative inputs (Shaw et al., 2008). As a result, various research teams are looking at the issue of effective communication of search results to the user and its impact upon the design process (Parmee and Abraham, 2006) (Grierson 2006).

2.1.5 Adapt to Different Building and Project Types

AEC projects typically differ with each project, varying by building type and size. To handle such diversity effectively, practitioners need a multidisciplinary optimization process that is flexible enough to support various information use cases, and scalable enough to apply at multiple detail levels (Lee, 2007). To support the process customization that is needed to meet these flexibility and scalability requirements, we believe the process should be modular. Modularity can be viewed as the ability to use old processes as the basis of new processes (Hargadon and Bchky, 2006). It should also have an open, documented and extensible data structure that does not require expert programming skills (Chaszar, 2003). Designers typically do not have such skills and must develop custom functionality for project-specific design requirements (Silver, 2006).

2.1.6 Visually Communicate Process and Information Dependencies

Practitioners are often unaware of how the information they produce will be utilized downstream or (potentially) in future design projects. New methods are required that enable the recording of information dependencies and demonstrating how design decisions impact long term goals (Haymaker, 2006) (Haymaker and Chachere, 2006). When using automated processes in design optimization, it is crucial to understand how certain results were derived for the purpose of rapid interpretation and consequent design decisions (Baldock, 2004). If a project team understands the automation routines, then team members can guide the construction and direction of the optimization process and propose alternative design solutions.

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

This section briefly discusses several design optimization techniques in the context of the AEC requirements outlined in section 2.1.

2.2.1 BEopt

BEopt uses the DOE2 (LBNL, 1982) and TRNSYS (TRANSYS, 2007) simulation engines and a sequential search technique to automate the process of finding optimal building designs (Christenson and Horowitz, 2006). The application includes a graphical user interface (GUI) that allows the user to select from a range of predefined and discrete building options (heating, ventilating, and air-conditioning system type, envelope constructions, etc.) 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 options and its inability to identify a wide range of objective functions.

2.2.2 OptEPlus

OptEPlus is an analytic framework that utilizes EnergyPlus (DOE, 2007) and various search routines to identify optimal buildings designs for energy usage (Ellis 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.

2.2.3 GENE_ARCH

GENE_ARCH is an evolution-based Generative Design System that 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 among multiple simulation engines.

2.2.4 GenOpt

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 (SPARK, 2007), BLAST (BLAST, 2003), 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.

2.2.5 Evolutionary Computing for Structural Optimization

Evolutionary Computing (EC) includes a variety of methods such as genetic algorithms, particle swarm analysis, cellular automata, ant colony search, etc. These methods have the power to sample and find areas of good performance in highly complex, multi-dimensional search spaces that typically occur in conceptual design (Parmee, 2001). There have been a number of research teams which have applied EC to the design of buildings (Sisk et al, 1999) (e.g. Kicinger et al., 2005) (Wang et al., 2006). All of these have focused on the structural aspects of the design, but consideration is also given in varying degrees to architectural and building service requirements. In addition, promising research has been done in encoding geometric logic into a parametric model linked to an EC tool in order to generate an array of possible solutions for a complex structure (Shea, Aish and Gourtovaial, 2003). More recently, Shea has done research on combining structural optimization of topology, shape and discrete section sizes in a relatively large structures (e.g. transmission towers) using structural grammars with simulated annealing (Shea and Smith, 2006). A criticism of the above systems is that they are unable to consider adequately the multi-objective nature of a design problem (Mora et al. 2006). In addition, they are not integrated with conventional CAD / CAE tools, requiring the designer to define the geometry and/or the structural analysis representation in an application they are not familiar with. In addition, these systems do not provide capabilities to adequately visualize multi-dimensional design spaces. Finally, these systems are limited in their visualizations of multi-dimensional design spaces, meaning each discipline must make design decisions in isolation, leading to poor integrated design solutions.

Although multidisciplinary design integration and optimization in AEC projects has demonstrated the power of integrated design and analytic processes to enable rapid iterations that lead to superior designs, these methods have not yet had a significant impact on the AEC industry practice. We suggest that in part this is because these methods do not fully address the multidisciplinary design and analysis requirements of the AEC industry.

2.3 PIDO Software Framework

According to Daratech, Inc. (Daratech, Inc. 2001) Process Integration and Design Optimization comprise software and design techniques intended to help engineers and analysts:

- 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 producea 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 several commercially available PIDO software frameworks against the requirements listed in Section 1.1, we selected Phoenix Integration's ModelCenter® process integration software to implement the case study. ModelCenter automates the process of running hundreds of design codes typically used during the design lifecycle. ModelCenter automatically transfers design data from one program to another, thereby allowing engineers to concentrate on design analysis, instead of the complexities of data integration. ModelCenter enables the construction of a design process easily through a series of linked applications with a simple interface. Software applications residing in different locations across a computer network can also be linked. This allows design teams, with member residing in different physical locations, to work together more easily. Once an integrated model has been built, ModelCenter's design exploration and optimization tools can be used to run the model, perform optimization and trade-off studies, and compare different design options. The next section describes our initial tests of the extent to which the PIDO methodology, implemented in ModelCenter, can satisfy the requirements of the AEC industry in the case study project example.

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). We evaluated the classroom design for its structural integrity, energy consumption, daylighting and 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.

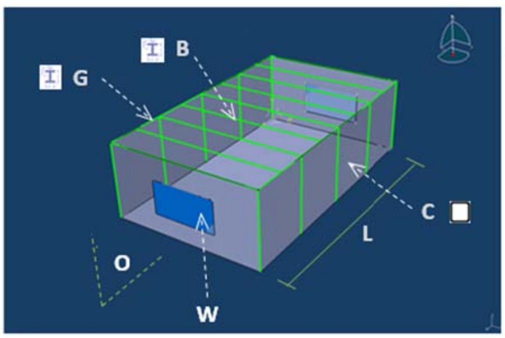
The objectives for the case study were to:

- Minimize capital cost of the building's steel frame
- Minimize 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 (Uniform Building 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.



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: Classroom Design Variables

The design process, optimization, and results will be presented in three parts: structural, energy, and combined structure and energy.

3.2 Structural Design Process, Optimization, and Results

The following section describes the geometric design for the structural model, the structural analysis process, the code checker, the structural optimization, and finally the results of the analysis. The structural model in ModelCenter is shown in Fig. 4.

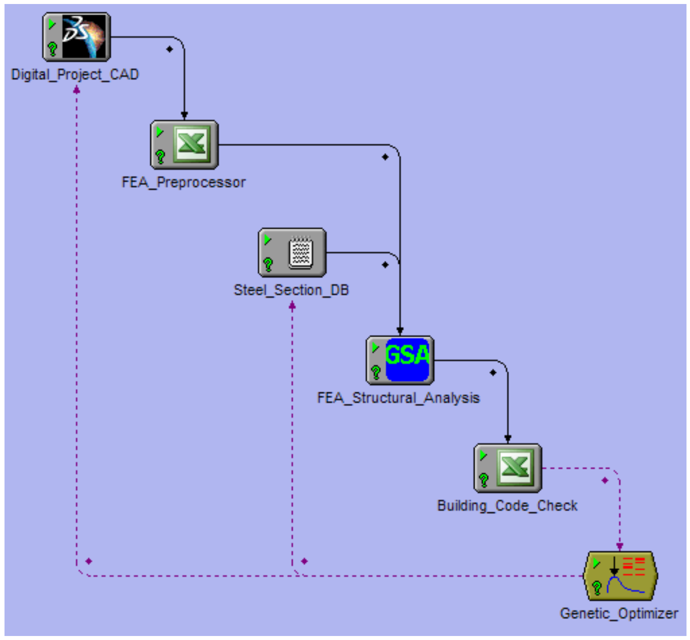


FIG. 3: Structural Model in ModelCenter

3.2.1 Geometric Design

The geometry for the process was created the parametric Computer-Aided Design (CAD) software Digital Project (Gehry Technologies, 2008).

The structural analysis representation consisted of centerline geometry for all of the structural members in the model. There were 9 beams spanning the roof, and 8 girders transferring the load to 12 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 member in the model. The area of these panels corresponded to the building area each member was responsible for supporting. This area updates automatically when the building geometry changes. The point coordinates defining the structural members and the loading panels are then passed on to the structural analysis software.

3.2.2 Structural analysis

The finite element analysis for the structure was performed using GSA (Oasys, 2008). Once the centerline geometry for the structural members is imported into GSA, all of the structural properties for the members including steel sections, 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 we specify all of this information, GSA calculates the forces and moments on the members in the model.

3.2.3 Structural code check and cost calculator

The structural code check and cost calculator is a custom written application written in Visual Basic. The code check component determines if the structural members have sufficient strength to resist the applied loading specified by the building code (Uniform Building 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. The FS was less than one if the particular section met all the structural design requirements and greater than one if it did not. 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) to improve computational performance. 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 are stochastic algorithms that utilize processes analogous to natural selection to 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 the globally optimal as well as near-optimal designs.

We configured the optimization problem in ModelCenter's genetic algorithm-based optimization tool called Darwin (Darwin, 2004). The approximate size of the design space for a section optimization study was 29,575 possibilities. 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 a moderately high performance PC.

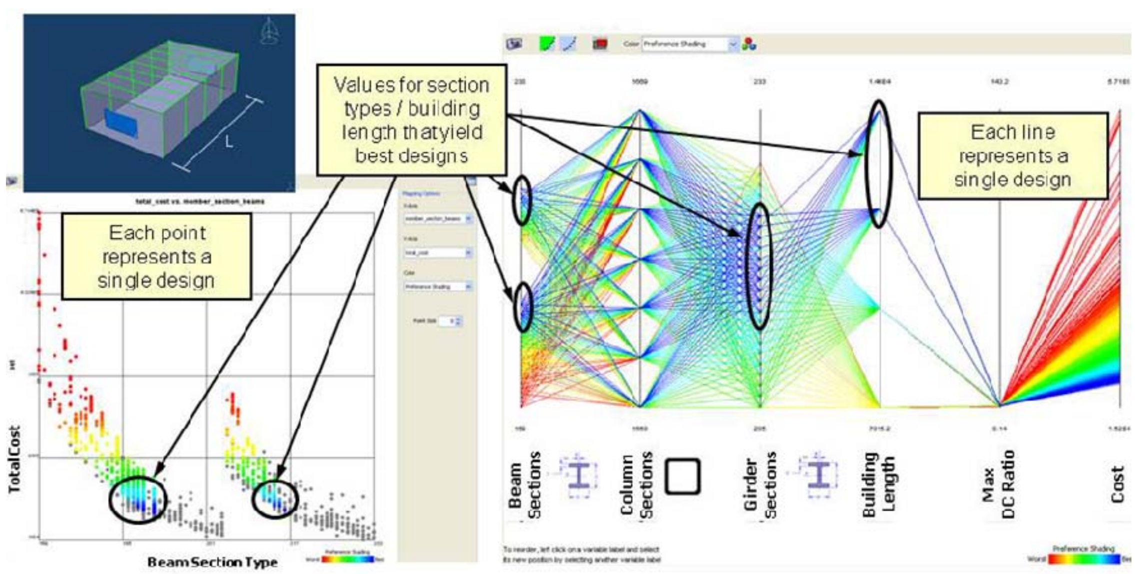


FIG. 4: Structural Optimization Results.

In Fig. 5, the scatter plot to the left 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 in the scatter plot. The best performing designs (i.e. cheapest designs that satisfy the constraints) are darker blue in color. 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 for 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.

The parallel coordinates plot in the right portion of Fig. 5 provides an alternative view of the design space that can also be used to interpret the results and validate the optimization process. In this plot, the range of values for each variable is represented as a vertical axis (increasing in value from the bottom of the axis to the top). Each colored line represents a different design. As in the scatter plot, lines that are darker blue in color represent the best designs. The point where each lines 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 sizes in the two depths considered (as shown in the left chart). The best (blue) designs also pass through the entire range of column sections, indicating that the choice for column size from the available options 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 the roof beams are simply supported and governed by gravity loading. The maximum bending moment for the roof beams in this case can be determined by the following equation:

$$M = (w \times S^2) / 8$$

Where;
M = bending moment (k×ft)
S = beam span (ft)
w = loading (k / ft)

From the equation we can see that the loading value (w) has a first order effect while span (S) has a second order effect upon the maximum bending moment. 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, we would expect the maximum bending moment to decrease as the building gets longer, allowing for lighter beam sections and a cheaper overall design. This is confirmed by the parallel coordinates plot.

3.3 Energy Design Process, Optimization, and Results

This section describes the geometric design for the energy model, the energy analysis process, the energy optimization, and the results of the analysis. The goals of the thermal simulations in EnergyPlus were to:

- Evaluate the ability to transfer design information from a parametric CAD tool to an energy simulation engine without the use of an intermediate data schema
- Generate a Design of Experiments (DoE) to visualize a representation of the entire design space
- Evaluate the sensitivity and transparency of performance trends from the DoE based on changing design parameters
- Compare the results of a design space optimization to the results obtained from the DoE in terms of simulation time requirements and accuracy

The energy model in ModelCenter is shown in Fig. 6.

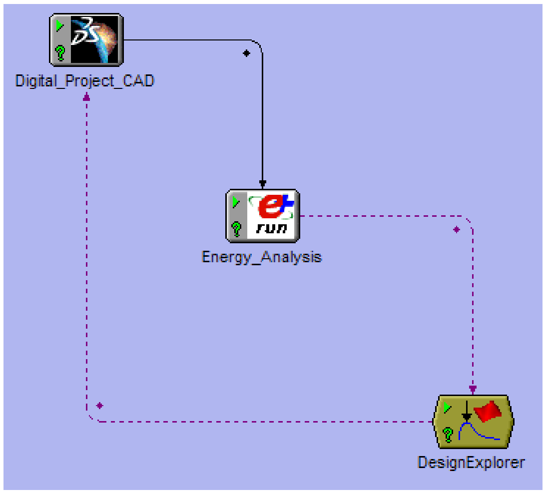


FIG. 5: Energy Model in ModelCenter

3.3.1 Geometric Design

The geometry for the process was generated using the same Digital Project model described in section 2.2.1. The independent variables in the energy geometry model were building length and window-to-wall ratio (See Fig. 2).

The energy model was a rectangular room with two windows on the grid east and west walls. The window was centered on the walls with the window area set to the product of the wall-area and the window-to-wall-ratio parameters. The aspect ratio of the window was kept the same as that of the wall containing it. A daylighting sensor location point was placed in the center of the room two feet above the ground level. Wall, roof, and floors surfaces were modeled without a thickness, minimizing the number of node coordinates needed to define the element geometry. Four node coordindates for each wall and window surface, and the daylighting sensor were then passed onto EnergyPlus.

3.3.2 Energy analysis

For the thermal performance software, we evaluated DOE-2, EnergyPlus, eQUEST (Hirsch, 2006), ECOTECT (Roberts and Marsh 2001) and IES (Pollock, 2007). We chose to use the simulation engine EnergyPlus because it combines several features of its predecessors to provide a more integrated and robust prediction of energy performance. The thermal runs simulated the energy requirements to maintain a space temperature of 70-73^{o}F between 7am-4pm Monday-Friday (operation hours for the classroom) with setbacks of 50^{o}F and 90^{o}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 packaged terminal air conditioner (PTAC) with gas heating and electric cooling. The lighting load was set at 1.5 watts/ft2, the equipment load at 1.0 watts/ft2, 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 modeled as argon filled double pane and low-e. A daylighting sensor was centered in the space at a height of 2.6 feet.

Before the generation of EnergyPlus input files could be automated for optimization purposes, an initial EnergyPlus input file was created using Graphisoft's ArchiCAD, IDF Generator, and IDF Editor. Using an IFC export of the model, the geometry was converted from ArchiCAD into EnergyPlus syntax using IDF Generator, a tool developed by LBNL (Maile and Bazjanac, 2008) (Bazjanac, 2008). All remaining non-geometric input file information required for the energy simulation (HVAC system, internal loads, operating schedules, etc.) were defined in IDF Editor (LBNL, 2008). Once the input file was generated and validated, the input file was converted into the EnergyPlus input macro file format. The functionality to change the building element geometry and the location of the daylight sensor was then added to it, along with the ability to change the building orientation. For the process to be automated, the EnergyPlus input file had to be modular 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.

3.3.3 Energy optimization

A Design of Experiments (DoE) was conducted to evaluate a performance trends over the entire spectrum of the design space. The DoE tool in ModelCenter is 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 for performing more sophisticated model methods like optimization. For each of the input variables, a starting value and an ending value was specified. 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 design was used and consisted of 1881 different designs.

As part of the research objective, it was also desired to compare the results of the DoE with the results of the optimization to evaluate differences in the two methods in identifying the best performing designs and the required simulation time for each method. A gradient-based algorithm was chosen to perform the optimization study because the optimization formulation comprised a single objective and continuous design variables. As mentioned previously, in general gradient-based methods are not ideal for the AEC industry, in particular for thermal performance. However, the exclusion of common discrete variables such as construction and HVAC system type made a gradient-based method more appropriate. The algorithm chosen was called Design Explorer (Phoenix, 2004). Design Explorer is a sophisticated optimization algorithm 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 (Kriging 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 single objective function for the optimization was to minimize total life-cycle operating costs. The design variables were building length (lower bound=4m, upper bound=14m), window-to-wall ratio (lower bound=0.1, upper bound=0.9), and orientation (lower bound=0, upper bound=180). The performance constraint was an upper bound of 0.6 for the annual average lighting power multiplier, and a lower bound of 0.01. The lighting power multiplier is the fraction of artificial lighting that is required to meet the design illuminance in the space (a lighting power multiplier of 0 means the space is completely daylit and 1 being completely lit by artificial lights) (LBNL, 2008).

3.3.4 Results

We explored the design space from a wide range of perspectives using the data generated by the Design of Experiments (DoE) including surface charts to understand general trends and glyphs charts to study data point spreads. Such visualizations were found effective for understanding performance tradeoffs between interactive and often conflicting thermal processes. In our particular case study, the tradeoffs between daylighting performance and energy performance by varying window size, building length, and orientation were evaluated. Larger windows generally result in improved daylight in the space. This allows for 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.

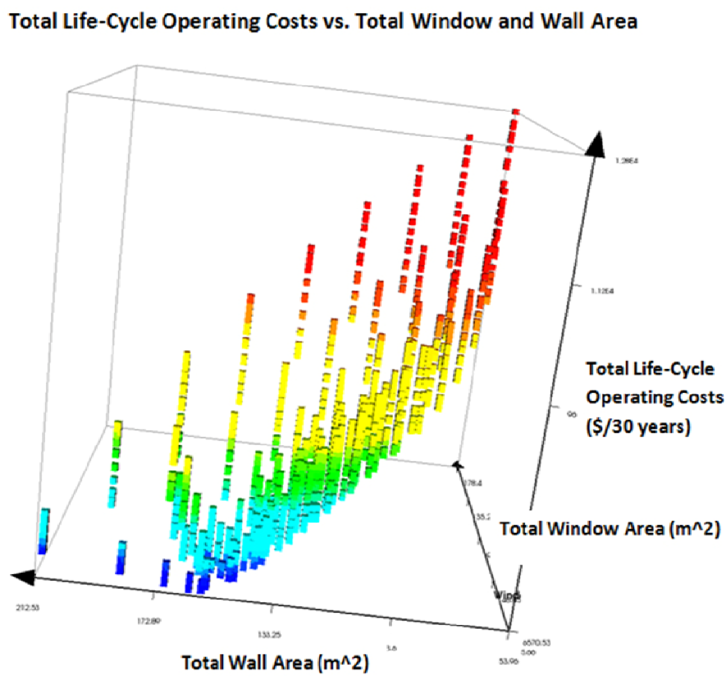


FIG. 6: Glyph Chart of Building Performance Trends

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 in the glyph chart represents a design option evaluated, with the blue designs representing the best designs and red designs the worst. 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.

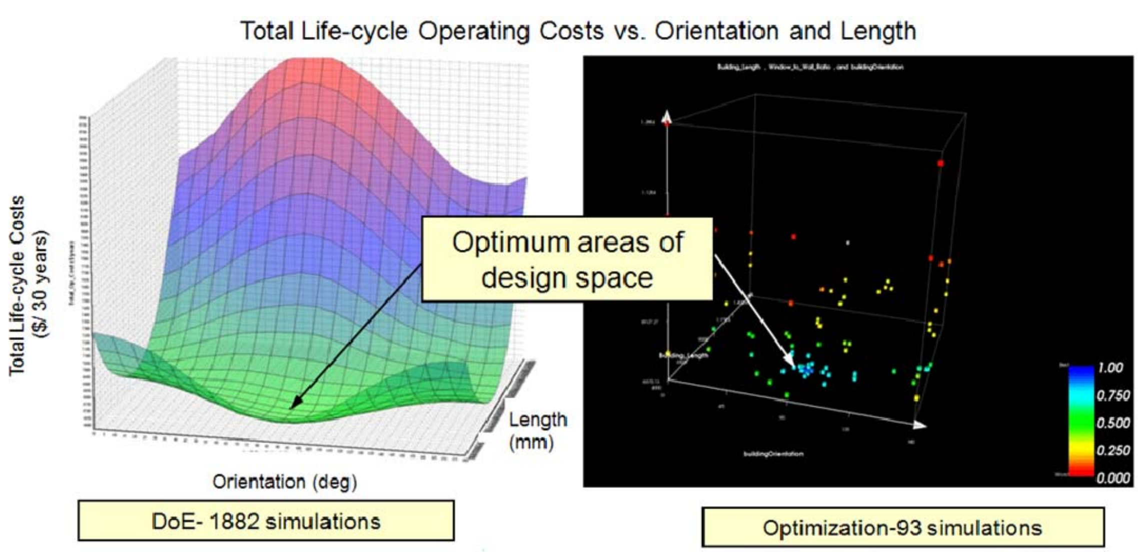


FIG.7: DoE Results vs. Optimization Results

Fig. 8 shows the results of 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. Simulation time to achieve the optimum design was reduced from 1881 simulations to 93 simulations (95%).

3.4 Multidisciplinary Optimization and Results

The following section describes the multidisciplinary optimization and the results of the combined energy and structural analysis.

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 to perform the multidisciplinary optimization study. For multi-objective problems, Darwin will generate a Pareto trade-off curve. The points lying on the Pareto curve are all optimal in the sense that they each represent a design point for 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 (10 degree increments), the building length varied from 4-14 meters (1m increments), and window-to-wall ratio from 0.1-0.9 (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 55,000,000 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 multidisciplinary model in ModelCenter is shown below.

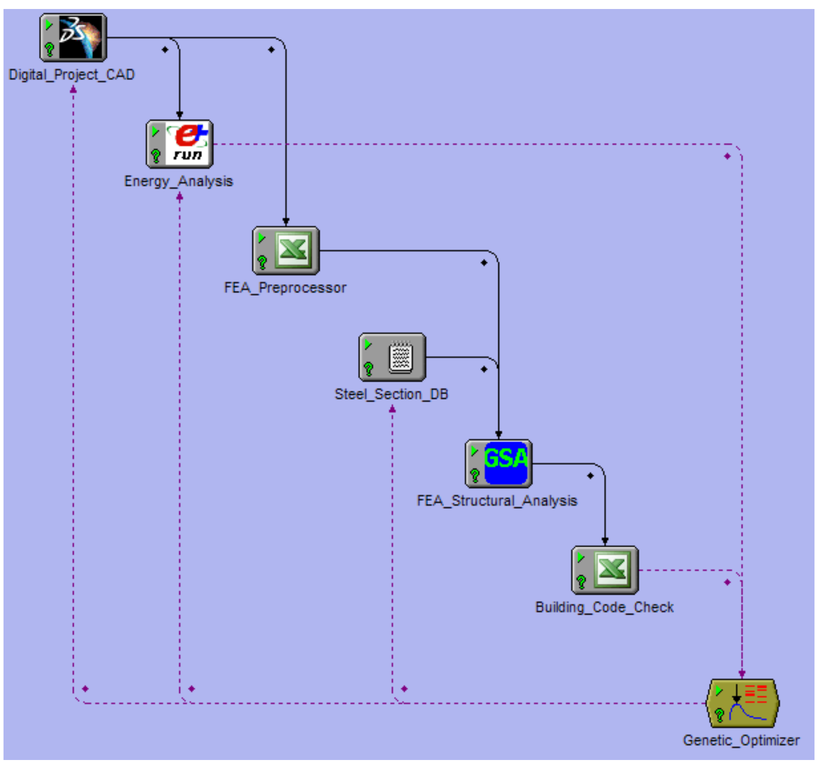


FIG. 8: Multidisciplinary model in ModelCenter

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 the same moderately high performance desktop PC.

The trade-off between structural costs and energy (operating) costs is shown in Fig. 10 below. 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 completing a large number of design iterations is it possible to accurately characterize (1) the trade-off between first and life-cycle costs as well as (2) the impact of building length upon first and life-cycle costs of the building (Fig. 11). These figures are examples of how designers can use PIDO methods to understand the performance trade-offs for a given design decision, allowing them to make more informed decision

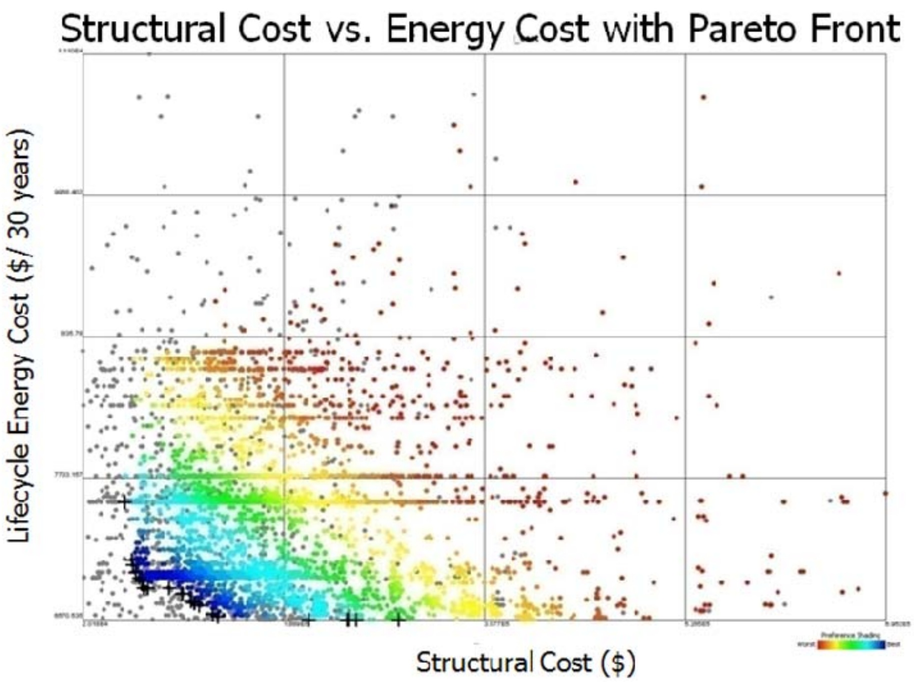


FIG. 9: Pareto front showing the trade-off between minimizing life-cycle energy costs and structural first costs.

Fig. 11 shows the impact of varying building length upon the cost of the steel frame as well as the operating costs. The designs marked with a '+' are Pareto optimal designs. From the figure, we see that the cost of the structure decreases as the length of the building increases. As discussed in section 3.2.5, this is because as the length of the building increases, the beam span is reduced, which results in a more efficient (and cheaper) structural frame. From the perspective of operating costs, however, the building becomes less efficient as the length gets longer. This is due to several factors including greater surface area of building skin, resulting in greater conductive losses, and a larger wall area for windows, resulting in increased solar gains and resulting cooling requirements.

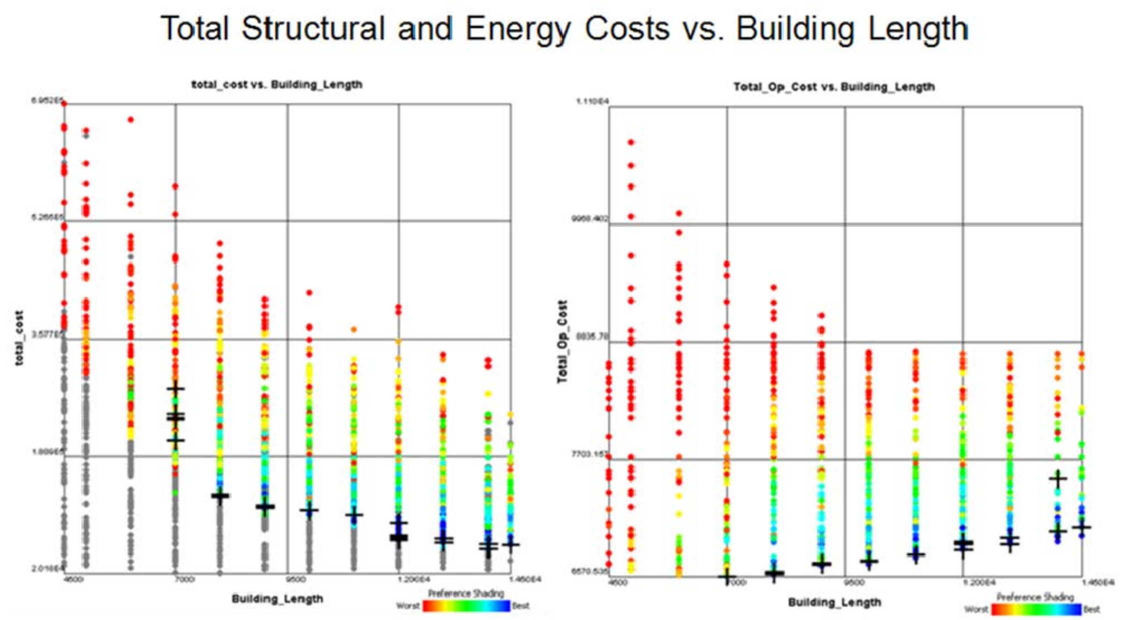


FIG. 11: When structural costs (left) and energy costs (right) are plotted against building length, the Pareto optimal designs show opposite performance trends.

4. CONCLUSIONS AND FURTHER WORK

AEC practice today typically generates and analyzes a very small number of design options before choosing a final design. Design theory argues this leads to underperforming designs. The aerospace industry has overcome similar limitations using PIDO, resulting in improved processes and product performance. For the AEC case study presented, we found that PIDO enabled orders of magnitude improvements in the number of design iterations compared to conventional methods. Instead of the customary two to three design iterations in a typical design project, using PIDO we were able rapidly to analyze over 5,000 design options and to choose from a range of near-optimal solutions. We now discuss our observations with respect to the requirements we outlined in section 2.1.

1) <u>Integrate with conventional CAD/CAE tools.</u> ModelCenter was able to integrate and automate the applications that the design team selected. The only requirement was that the application be able to run in batch mode. We needed software development expertise to write the wrappers required, a skill which is not common among architects and civil engineers. Once wrappers have been written, however, engineers and architects can create new processes, leverage optimization algorithms, and visualize results by interacting with ModelCenter through its graphical user interface. 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.

2) <u>Rapidly generate and analyze alternatives.</u> Alternatives were automatically and rapidly generated using the parametric model in Digital Project. The challenge for the design team was in creating and integrating the geometry for the analysis representation into Digital Project using 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 parameters. Once this was accomplished, ModelCenter successfully integrated the parametric model into the rest of the process. In this case study, the space of alternatives we explored was limited as the class room was geometrically simple and we did not explore topological differences in geometry. Future work should test various alternative generation techniques, including those for topology changes, and assess how well they lend themselves to integration in the PIDO environment.

   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, 1999). The limiting factor was, however, the time required to integrate such tools with ModelCenter. On this project, we took approximately 40 man-hours to integrate EnergyPlus, 100 man-hours to integrate GSA, and 30 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. Future work should test how general the wrappers are, and to measure and compare the development time necessary to automate the process with the benefits gained through such automation.

3) Apply 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 Design Explorer, a gradient-based method which had continuous variables, for the energy optimization analysis. A Genetic Algorithm was used for the multidisciplinary optimization. The optimization methods worked well for given problem. Further research is needed to examine whether these optimization methods are capable of tackling larger, more complex ACE design problems or whether new methods will be required.

4) Visualize trade spaces. We used advanced plotting tools for multi-dimensional visualization, including glyph, parallel coordinates, scatter, and histogram. 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 (e.g. 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.

5) Adapt to different building and project types. We believe the wrapper written for GSA and the structural code checker is generally applicable to structural strength design of steel framed structures of any scale. The macro-based system to integrate Digital Project and EnergyPlus lacked flexibility and scalability (e.g. if more spaces were added to the CAD model, the macro files would not run). However, the limitations of the EnergyPlus wrapper were due to our chosen implementation strategy (macro-based), and not to any limitation of the ModelCenter framework. Future work will examine the robustness and scalability of the PIDO approach by testing the technology and methods on larger and more complex projects using more intelligent script wrappers.

6) Visually communicate process and information dependencies. ModelCenter contains a high level process model as shown in Fig. 9, and it is possible to further interrogate this model and determine the data dependencies. We found it helpful to supplement these descriptions of process and data interoperability with more detailed models constructed in Visio that explicitly visualized the process model and data exchanges together, and identified the actors responsible for each step in the process. 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 process, and the testing of the extent to which they assist design teams to more easily design and manage PIDO processes.

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 options; 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.

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