

Title:

An Interactive Expert System for Daylighting Design Exploration

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Abstract: (150-250 words)

Architects increasingly use digital tools during the design process, particularly as they approach such complex problems as designing for successful daylighting performance. However, while simulation tools may provide the designer with valuable information, they do not necessarily guide the user towards design changes which will improve performance. This paper proposes an interactive, goal-based expert system for daylighting design, intended for use during the early design phase. The expert system consists of two major components: a daylighting knowledge-base which contains information regarding the effects of a variety of design conditions on resultant daylighting performance, and a fuzzy rule-based decision-making logic which is used to determine those design changes most likely to improve performance for a given design. The system gives the user the ability to input an initial model and a set of daylighting performance goals in the form of illuminance and daylighting-specific glare metrics. The system acts as a “virtual daylighting consultant,” guiding the user towards improved performance while maintaining the integrity of the original design and of the design process itself. Two sets of case studies are presented: first, a comparison of the expert system results to high performing benchmark designs generated with a genetic algorithm; and second, an evaluation of the expert system performance based on varying levels of aesthetic constraints. The results of these case studies indicate that the expert system is successful at finding designs with improved performance for a variety of initial geometries and daylighting performance goals.

Keywords: Expert system, daylighting, design process

1 Introduction

Designers have long considered daylight as an important aid for architectural expression. In recent decades, we have come to understand that daylighting may provide additional benefits, such as reduced energy consumption and improved occupant health and well-being [1,2,3]. Nevertheless, simply providing daylight in a building will not always result in positive results. Daylighting is only as good as its delivery system, so careful design is necessary to ensure that enough light is available and that glare, shadows, and reflections are reduced [4]. Unfortunately, it is often a challenge to create a successfully daylight building.

Digital tools offer new ways of helping architects create or find designs with high levels of daylighting performance using efficient and intelligent guided design exploration methods. Optimization algorithms are a common solution, largely because they have the capabilities necessary to find or generate successful solutions; however, these methods generally allow only limited amounts of user interaction during the actual optimization or decision making process. Optimization algorithms also produce solutions based on performance criteria, not based on any understanding of design. As it is highly unlikely for a designer to simply accept a design generated by an optimization algorithm, an alternative approach would be a more interactive search method, which would accept input from a designer and grant the designer a larger degree of control.

An example of such an approach is a knowledge-based or expert system. An expert system is one in which human expert knowledge about a specific domain is encoded in an algorithm or computer system [5]. In the daylighting domain, such a system would function as a virtual lighting consultant, guiding the designer towards design modifications which improve overall daylighting performance. Knowledge-based systems have already been successfully implemented for artificial lighting scenarios [6,7]. For daylighting, a few simple expert systems exist. The Leso-DIAL tool uses an expert system based on fuzzy logic rules to provide users with a “qualitative diagnosis” (for example, it might diagnose the light levels in a space as “Very Low” and suggest modification of certain design characteristics) [8]. The NewFacades approach considers energy and visual comfort based on a prescription energy code for hot climates to suggest a range of façade solutions to the designer [9]. These systems represent first steps in expert systems for daylighting in design, but they do not allow for a comprehensive understanding of daylighting or a large amount of user interactivity regarding design choices.

This paper describes a user-interactive expert system approach which includes two climate-based performance metrics, one for illuminance and one for daylighting-specific glare, in order for the designer to have an understanding of the amount of light and the visual comfort in the space. The method begins with a designer's own initial design and performance goals. It then evaluates the performance of the design and creates a series of

suggestions for design changes which are likely to result in improved performance, thus enabling a search process that is highly specific to the user's design problem. The expert system is comprised of a pre-calculated database of daylighting-specific information connected to a set of fuzzy daylighting expert rules. Any design decision that the designer chooses to allow will be automatically generated in the original model and the new performance will be calculated. The designer is allowed to interact with the system through an iterative search process that is both agreeable to the designer and likely to improve the performance of the design.

The effectiveness of the proposed expert system as a design-making algorithm has been assessed through a series of case studies which compare the performance of designs found by the expert system to a set of reference designs generated by a genetic algorithm, a known optimization method. The behavior of the expert system was also evaluated based on façade design constraints, including the initial façade designed by the user and the selected window uniformity scheme (which describes whether the expert system must constrain all windows on the façade to have the same dimensions or whether windows may differ from one another). The results of these case studies are presented in this paper and indicate that the expert system is successful at finding good solutions for a variety of performance and design conditions.

2 Expert System Development

The expert system presented in this paper is a fuzzy rule-based system combined with an external database of previously computed daylighting simulation data. This external database serves as a “knowledge base” of information about how various changes to façade design elements, such as window size and external shading devices, affect the illuminance and glare in the interior of a space. The fuzzy rule-based system uses information from this database in addition to information about the geometry and daylighting performance of a given design to create a list of suggested façade design changes that should improve overall daylighting performance. This section describes the major components and logic used by the expert system.

2.1 Overall System Structure

The expert system was developed as an extension of the Lightsolve program, an intuitive rendering and simulation tool aimed to help designers consider daylighting performance in the early design stages [10]. A schematic of the overall expert system is shown in Figure 1. The process begins when the user inputs information about his or her specific design problem into Google SketchUp. This data includes a 3d model, location information, and specific daylighting performance goals for illuminance and glare. The next steps of the process are to populate a simple building data model based on the 3d model which will be used by the expert system as well as to determine the performance of the design using a daylighting simulation program. The user's specific performance goals are taken into account using goal-based metrics which are calculated using the simulation data. The expert system component of the system consists of a series of fuzzy rules which use information about the current goal-based performance as well as the

geometry and materials used within the design to create a list of façade-specific design changes to suggest to the user. The user is allowed to view this list, along with the current performance of the design, in an interactive interface that was developed specifically for the expert system. The user may choose a design suggestion to try from within the interface, and the system will automatically make the selected change to the original 3d model. The process then repeats until the designer is satisfied with the design.

Each of the major components of the expert system are described in further detail in the following sub-sections: the 3d modeler (section 2.1.1), the user inputs (section 2.1.2), the simulation engine and daylighting metrics used by the system (section 2.1.3), the building data model (section 2.1.4), the user interface (section 2.1.5), the knowledge-base of daylighting-specific information used by the expert system (section 2.1.6), and the major assumptions and logic used within the fuzzy logic rule bases for decision making (section 2.2).

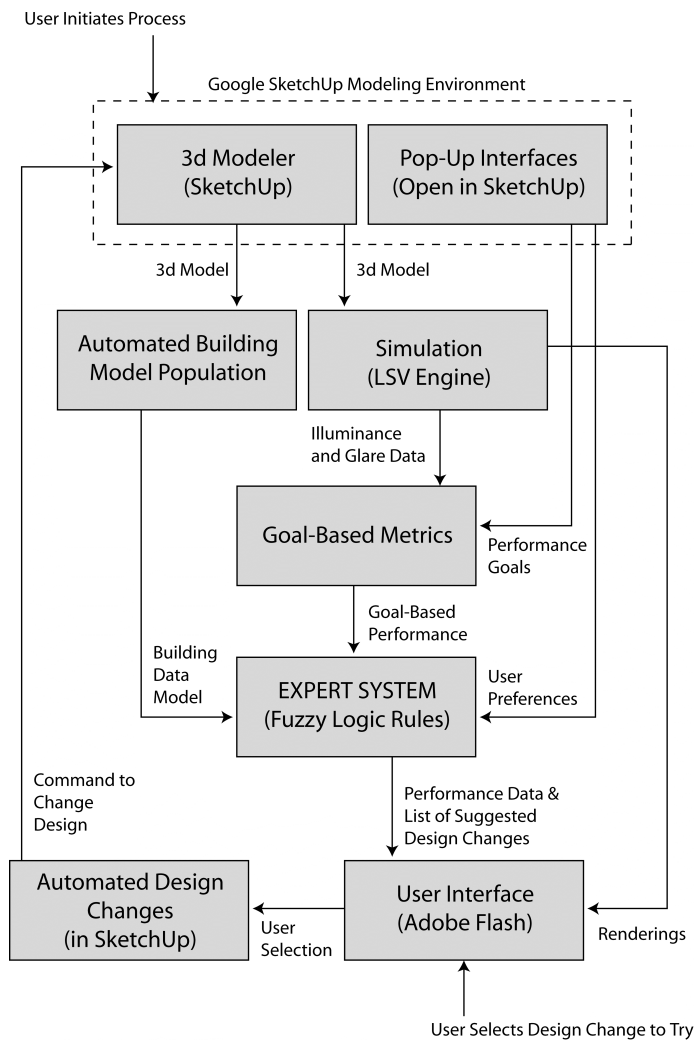


Figure 1: Overall system diagram of the expert system.

2.1.1 3d modeler

The 3d modeler currently used by the system is Google SketchUp [11]. This program is an intuitive and robust modeling tool with an embedded Ruby application programming interface (API), which was used to develop the majority of the expert system functionalities. The expert system process can be initiated from within SketchUp after the user creates a 3d model of his or her design.

2.1.2 User Inputs

The expert system requires a number of initial user inputs that describe the design problem. The major user input is a 3d model of an original design in SketchUp. Sensors for illuminance and/or glare are modeled as 2d planes. The user may elect to have any number of illuminance and/or glare sensor planes and they may be any size. Sensor planes may be oriented vertically or horizontally, and they may be opaque or transparent. Materials of opaque and glass surfaces must be specified within SketchUp. An example model with horizontal illuminance sensor planes and vertical glare sensor planes is shown in Figure 2.

The Ruby API embedded within SketchUp was used to create pop-up interfaces that allow the user to enter such additional inputs as performance goals for each sensor plane. For each illuminance sensor plane, the user must specify a desired illuminance goal range in lux, including the actual desired range and a buffer zone of acceptable values. For example, the user may desire the illuminance of a given sensor plane to fall between 400 lux and 1200 lux, but he or she will also accept illuminances as low as 200 lux and as high as 1500 lux. For each glare sensor plane or glare sensor group, the user must choose a glare tolerance. The glare tolerance options are “zero” (i.e. no glare is tolerated), “medium”, and “high” (i.e. a high amount of glare is allowed).

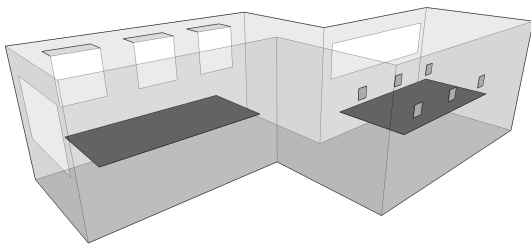


Figure 2. Example 3d model that meets expert system modeling criteria. Interior illuminance and glare sensors are shown as horizontal and vertical planes, respectively.

Additional inputs allow the user to customize the behavior of the expert system. One set of inputs is the set of priority levels for each performance goal. The priority level is a number from 1 to n , where n is the total number of sensors. The user may choose to prioritize one or more goals over others, or he or she may elect for all goals to have the same priority.

The user may constrain the expert system aesthetically by selecting a window uniformity scheme. Three choices are allowed: “All windows in the model should look the same,” “All windows on a façade should look the same,” or “Windows can look different from other windows on the same façade.”

A location and weather file must be specified to provide climate data to the simulation engine. Weather data in an EnergyPlus weather data format (.epw) can be used by the system. Finally, the user must indicate his or her times and seasons of interest (the choices are: winter, fall/spring, summer, morning, mid-day, and afternoon). The expert system will only consider performance during those times of interest selected by the user.

2.1.3 Simulation Engine and Daylighting Metrics

The engine used to calculate daylighting performance is the Lightsolve Viewer (LSV) [12], the rendering and simulation engine native to the Lightsolve program. LSV is a hybrid global rendering method that combines forward ray tracing with radiosity and shadow volumes rendering. It is a stand-alone executable which is called directly from within the SketchUp/Ruby environment and simulates the performance of 3d models created in SketchUp.

For all illuminance and glare sensor planes within the 3d model, the LSV engine calculates annual goal-based performance metrics using the 3d model, the location and weather information, the performance goals (illuminance ranges and goal thresholds), and the times of interest. To calculate the goal-based illuminance, the LSV engine first triangulates each sensor plane into small patches, and then calculates climate-based illuminance [12] on each patch over 56 time periods that represent a whole year. For a single patch, the goal-based illuminance metric is defined as the percentage of the user’s times and seasons of interest during which daylight provides an illuminance within the user’s specified range. The final goal-based illuminance for a sensor plane is an average of the performance over all patches on a sensor plane. Partial credit is given for illuminance levels that fall between the “acceptable” and “desired” values (Figure 3). A value of 100% indicates that the entire area of the sensor plane sees an illuminance in the user’s desired range over all periods of day and seasons of interest.

Similarly, goal-based glare is calculated on each glare sensor over 56 time periods that represent a whole year. The glare metric used by the expert system is Daylight Glare Probability (DGP), which indicates the percent of occupants disturbed by a daylighting glare situation [13]. DGP was chosen because it is a daylighting-specific glare metric that considers windows as glare sources. DGP has also been found to yield the most plausible results for glare due to daylighting when compared to other glare indices [14]. The LSV engine calculates a model-based approximation of the DGP known as DGPm, which performs within a 10% error of the DGP over 90% of the time for rectangular models that do not include window frames [15].

To evaluate glare risks, the expert system uses the DGP threshold values described by Wienold [16], where any value below 0.33 (imperceptible glare) is considered a “no glare” situation and given a glare credit of 100%. The threshold values for these three glare tolerance levels (“zero”, “medium”, or “high”) correspond to the three glare ratings of “perceptible”, “disturbing”, and “intolerable” glare [16]. Any calculated glare value above the upper threshold is given a glare credit of 0% (Figure 3). These glare credits are averaged across all glare sensors in each glare sensor group within the model. A value of 100% indicates that the specified view direction is unlikely to see glare due to daylighting.

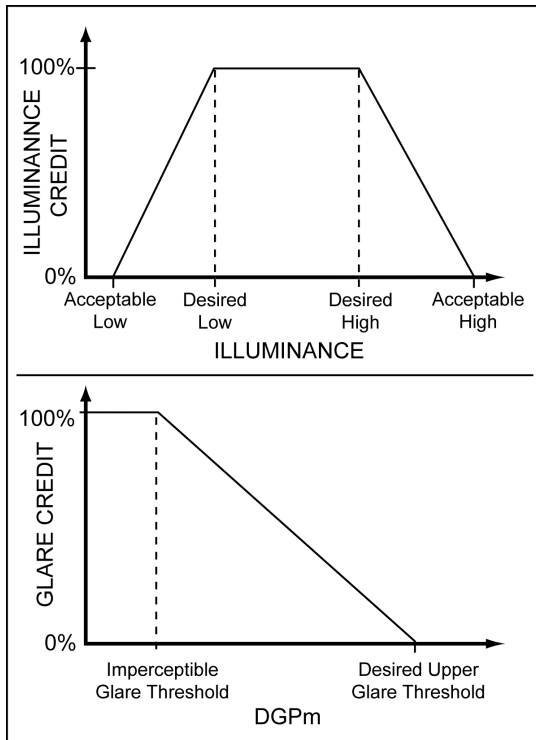


Figure 3: Functions for goal-based performance metrics for illuminance and glare

2.1.4 Simple building data model

In addition to performance, it is necessary for the expert system to understand the geometry and materials of the design. To accommodate this, a simple building data model was developed whose values are automatically assigned once the process is initiated. The model contains information about each building element (floor, wall, ceiling, window, shading device) and the relationships between them. Each building element object contains information about its location, geometry, orientation, and material. The general structure of the data model is indicated in Figure 4.

The building data model was implemented using the SketchUp Ruby API and is created using 3d models in SketchUp. The logic used to populate the building data model is described further in [17]. The model allows the expert system to understand which walls have windows, how large those windows are and where they are oriented relative to each

other, as well the shading devices and glazing associated with each window. It also allows the system to understand the locations of each illuminance or glare sensor relative to each façade and to each individual window on the façades.

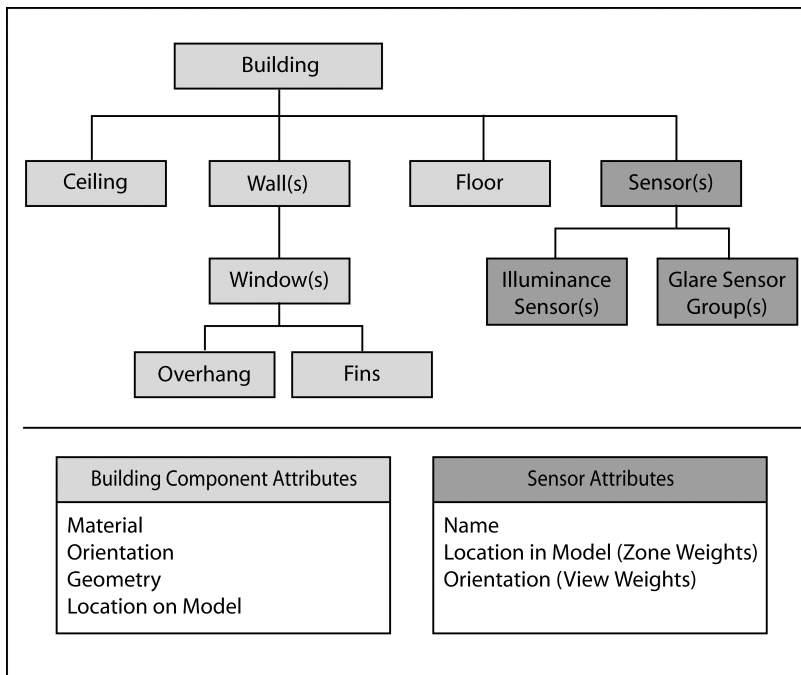


Figure 4: Structure of simple building data model automatically generated by the expert system based on a 3d model

2.1.5 User Interface

A stand-alone interface was developed to allow the user to interact with the expert system. The interface indicates the current performance of the design based on the goal-based illuminance and glare metrics and displays the design changes suggested by the expert system to the user. The interface also allows the user to select design changes to implement based on the expert system's suggestions. The user's selected design changes are automatically applied to the user's 3d model in Google SketchUp and simulated using LSV. Once the simulations are completed, the interface is updated with the performance of the new designs and a new list of design suggested is displayed. The interface will continue to update to display the performance of the designs over multiple iterations (Figure 5). This interface was implemented using Adobe Flash.

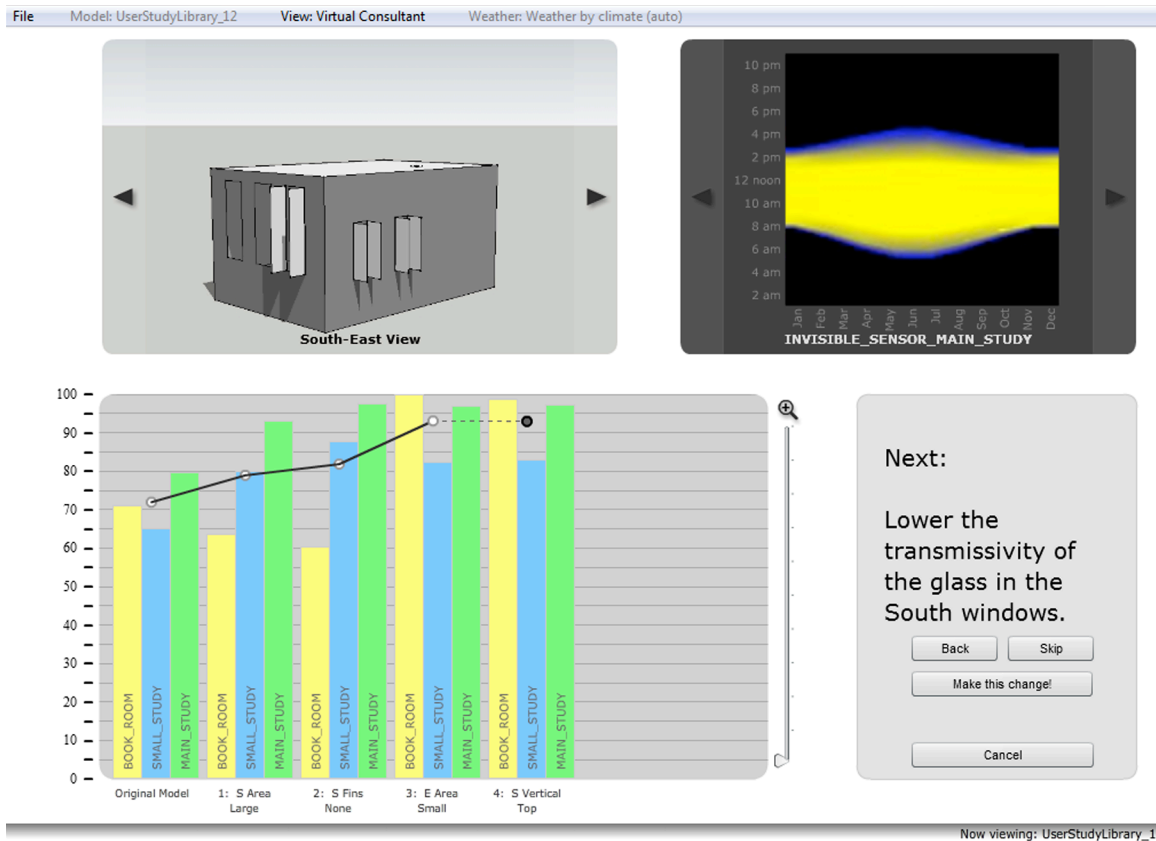


Figure 5: Performance analysis and decision making interface for the expert system. Views of the current design are shown (top left) along with annual performance in temporal map form (top right). Performance over multiple iterations is shown in the interactive graph (lower left). Expert system design suggestions are given in the lower right.

2.1.6 Daylighting Knowledge-Base

To aid in the decision-making process, the expert system uses a knowledge-base of pre-calculated, climate-specific data [18]. This database was populated with simulation data, using the Design of Experiments method [19]. It contains information about the relative effects of 10 different façade parameters on both illuminance and glare from the various zones and views within the space. The 10 different façade parameters considered are: window area, window height-to-width ratio, vertical and horizontal location of windows on the façade, window distribution (how close or far apart windows are to each other), total number of windows, length of horizontal overhangs and/or vertical fins, glass transmissivity, and glass type (regular or translucent). The expert system can potentially suggest 20 different façade design changes, which correspond to two directions of change for each of the 10 façade parameters considered in the knowledge base (for example, window area can be made larger or smaller).

The expert system uses the information within the general daylighting knowledge-base to create a customized database which includes only the data corresponding to the seasons and times of interest given by the user. This subset is further customized for each individual sensor based on the zones in which each sensor is located. Additionally, only

the relevant views are included for glare sensors. For example, a user may create a 3d model in which glare sensors are placed facing south-west from within the core and south perimeter zones. The user might also specify that his or her goals are relevant only during the school schedule. In this situation, the expert system would only use information from the knowledge-base which is relevant to glare sensors facing south and west from core and south zones during autumn, winter, and spring, from early morning through early afternoon only. All additional information, such as data about glare sensors facing north, data about the summer months, or data about illuminance sensors, would be ignored by the system.

2.2 Fuzzy Logic System

The expert system rule base is a decision-making algorithm that assesses specific design situations and creates lists of suggested design changes that should improve the current performance, based on user-defined daylighting goals. The rule base uses fuzzy logic [20], which allows it to better emulate the human thought process than classical logic. It has been developed to be a flexible algorithm that can accommodate a wide variety of initial design scenarios.

2.2.1 Assumptions and Logic

This section provides an overview of the general assumptions and logic used within the expert system to determine which design changes to recommend to the user to improve performance.

Selecting Which Windows to Target

The expert system assumes that design changes made to the façade closest to a given sensor will affect that sensor more than design changes made to façades further from the sensor. Similarly, the expert system assumes that on a given façade, some windows will be closer to a sensor plane than other windows, and changes to those windows will have a greater effect on the sensor plane than other windows on the same façade.

Dealing with Multiple Performance Goals

If there are multiple sensors within a model, the expert system will attempt to find design changes that are likely to improve the performance of all sensors at once. However, in situations where the user's goals are conflicting, the expert system will choose to improve one sensor at a time, perhaps at the expense of performance of another sensor. In these scenarios, the expert system uses the following logic: user-specified high priority goals take precedence over lower priority goals, and sensor planes that have the lowest current performance have priority over sensor planes with good current performance.

Dealing with Illuminance Goal Ranges

Illuminance goals are based on user-specified lower and upper bounds. As a result, an illuminance sensor plane may see illuminance that is too low, within range, or too high. Dealing with a sensor plane which sees illuminance that is both too high and too low at the same time is a complicated problem. The expert system chooses to deal with this problem in two ways: it determines if other sensors would benefit more from moving

towards higher illuminance or lower, and it takes into account whether the amount of illuminance that is too high is greater than or smaller than the amount of illuminance that is too low.

Determining an Appropriate Magnitude of Change

A problem similar to that of dealing with illuminance goal ranges is selecting an appropriate magnitude of change. For example, the system may conclude that a small increase to the illuminance on a sensor plane will bring performance closer to the user's goal range; however, an increase which is too large will result in decreased performance due to the illuminance on the sensor plane's being too high. The expert system deals with this issue by determining whether a change should be "small" or "large," and by selecting design changes from the daylighting knowledge base which are deemed most appropriate for that magnitude. The system then creates design changes in three increments and allows the user to select the version he or she prefers based on the resultant performance and aesthetics.

2.2.2 Fuzzy Sets and Rules

During the expert system process, the goal-based illuminance and glare performance of the design, along with the original user inputs, is used to assign values to sets of fuzzy variables, which help to describe the current scenario. These fuzzy sets are: userPriority (high and low), sensorPerformance (good and bad), illuminanceSensorPerformance (too high and too low), glareSensorPerformance (too high), and distanceFromPerformanceGoal (close and far).

In addition to these fuzzy variables, the system also uses information from the model's customized knowledge-base (section 2.1.6) to determine values of the fuzzy set actionResult (Figure 6) for each potential design change. These fuzzy variables refer to the likely result of a given design action on a given sensor, for example "Large Increase in Illuminance". Each sensor in the model will have a unique actionResult fuzzy set, with different values for each possible design change.

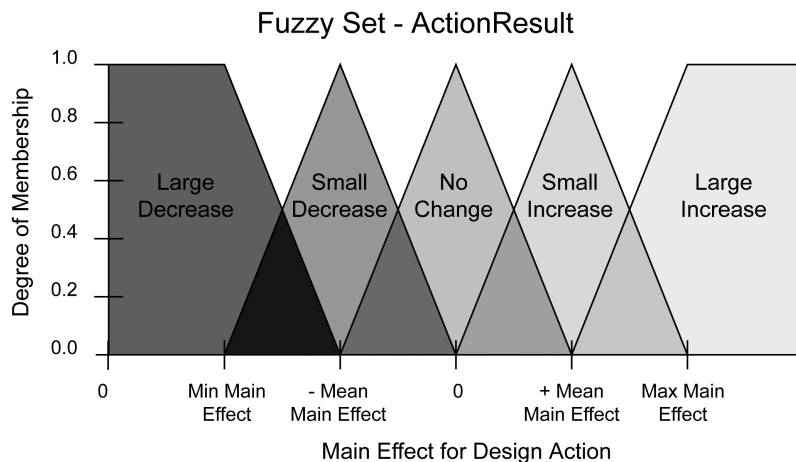


Figure 6: Membership functions for ActionResult fuzzy set.

Once created, the fuzzy variables are used to fire a series of fuzzy rules. The result of this process is a ranked set of design actions that are most likely to improve the performance of the current design based on the user's goals and preferences. Each individual fuzzy rule is an if-then statement which uses fuzzy variables for both the antecedents and consequents. The fuzzy rules have been divided into four sets of "rule bases" which are fired in the order indicated in Figure 7. Each rule base contains a series of fuzzy logic if-then statements which are fired in sequence. The purposes of each rule base, along with example if-then statements, are listed below:

Rule Base 1: Determine priority of each sensor. For example, one rule within this rule base is: IF SensorPerformance is Bad AND UserPriority is High, THEN SensorPriority is High.

Rule Base 2: Determine which change(s) will improve performance, based on the current scenario. For example, IF SensorPriority is High AND SensorType is Illuminance AND IlluminancePerformance is TooLow: (a) IF distanceFromGoal is Far, THEN DesiredChange is "Increase Illuminance by a Large Amount"; (b) IF distanceFromGoal is Close, THEN DesiredChange is "Increase Illuminance by a Small Amount".

Rule Base 3: Evaluate each possible design action in the customized database using the desired changes determined in Rule Base 2. For example, IF DesiredChange is "Increase Illuminance by a Large Amount" AND ActionResult is LargeIncrease, THEN action is GoodForSensor. These rules are fired once per potential action, and once per sensor.

Rule Base 4: Each potential action is ranked based on how likely it is to improve each sensor and the sensor priorities.

The final step is to sort the set of design actions from highest to lowest rank. The first design actions in the list will be those actions most likely to produce positive performance results in the current design, while those actions at the end of the list are likely to decrease overall performance. The expert system interface presents the design suggestions to the user one at a time in this order.

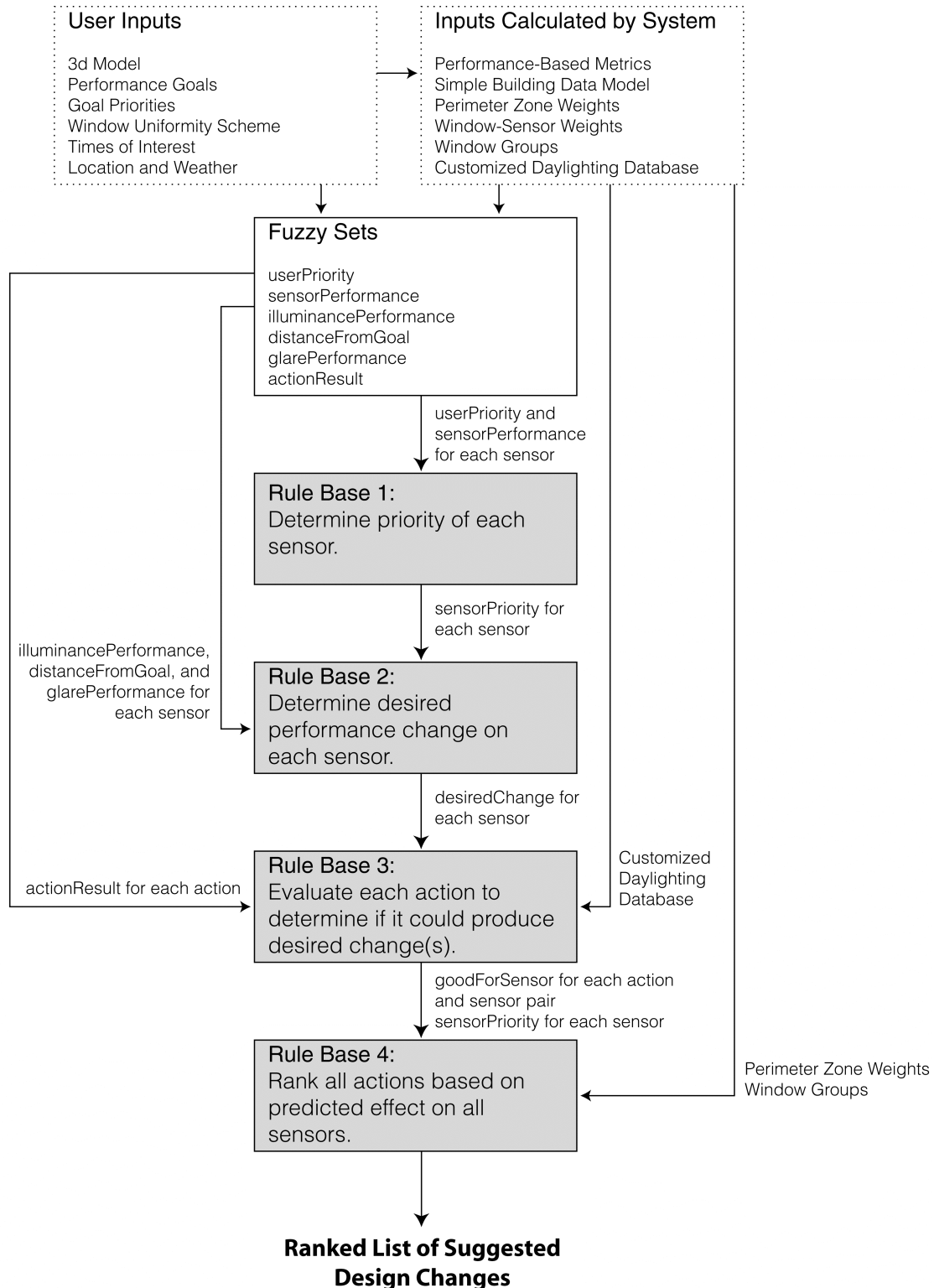


Figure 7: Flow chart for fuzzy logic rules fired by the expert system with inputs and fuzzy variables indicated. Each rule base represents a series of fuzzy if-then statements which are fired sequentially.

3 Evaluation of the Expert System

The main function of the expert system presented in this paper is to effectively guide a user towards improved daylighting performance of an original design. It is of critical importance that users have confidence in the advice given by the system, so a high level of performance is essential. Although the expert system differs from a traditional optimization algorithm due to its domain-specific and user-interactive nature, it should be equally capable of finding successful solutions in a best-case scenario.

In order to assess the behavior of the expert system, a set of studies was performed to compare the performance of designs found using the expert system to high performing benchmark designs generated using a genetic algorithm (GA). The GA was chosen to create the benchmark cases because it is an algorithm known to find optimal or near-optimal solutions for a variety of solution spaces; however, it should be noted that other optimization algorithms could have been used with the similar results. The GA used in these case studies was a micro-genetic algorithm (micro-GA) [22], which is a GA with a very small population size. For each case study, the objective function for the micro-GA was to maximize the goal-based performance of all sensor planes within the model. For comparison purposes, the micro-GA was implemented within the Lightsolve system and uses the same 3d models and performance metrics as the expert system. The same 10 façade variables were considered, encoded into a 30-bit string. These variables were the same variables considered by the expert system. For these case studies, no constraints were considered for either the micro-GA or the expert system. Further details about the micro-GA system can be found in [17].

Section 3.1 describes the results of a selection of case studies that demonstrate the behavior and performance of the expert system across a variety of scenarios. A more complete set of case studies can be found in [21]. Section 3.2 presents the results of two additional studies that were performed to determine how the behavior of the expert system is influenced by initial façade constraints, the façade design of the initial model and the window uniformity scheme selected by the user. All case studies were sited in Boston, MA.

3.1 Comparison Case Studies

A set of study procedures was developed to better compare results from the expert system to the GA, given their differences in algorithm type. While a GA generates designs, the expert system always assumes that an initial design is given and suggests design changes based on the current design. The following procedures were used:

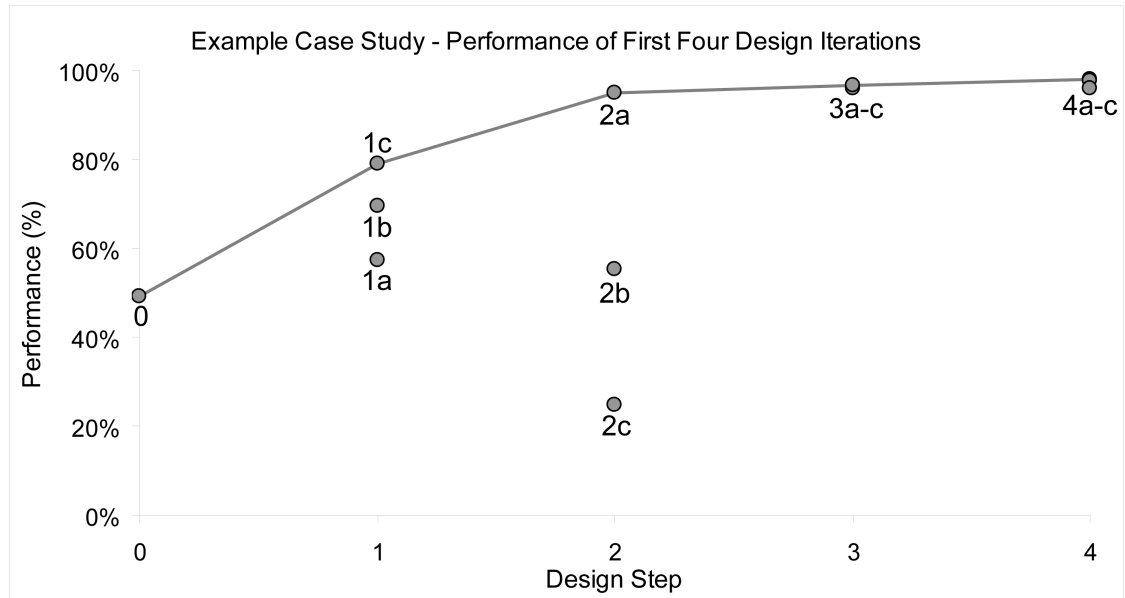
Micro-GA procedure

An initial massing model with no windows was used to generate a new model of each generated design. The algorithm was run for 10 generations before stopping. If a solution that met all goals was not found, the highest performance found over all generations was considered to be the best design. As the goal of the study was to generate a high-

performing benchmark design and not necessarily an optimal design, it was assumed that 10 generations were sufficient.

Expert system procedure

An initial model, designed to be of mediocre performance, was created with generic rectangular windows. For these case studies, a “perfect user” was assumed. The “perfect user” was defined as someone who would select the first suggested design change at each iteration and the best performing magnitude of each design change. This scenario is illustrated more clearly in Figure 8, which shows the first four design stages suggested by the expert system for case study #1 (section 3.1.2.1). The “perfect user” scenario was also one in which the process continued even if performance decreased after a given design iteration. The algorithm was run for 10 design iterations before stopping. As with the GA study, if a solution which met all goals was not found, the best design was considered to be that with the highest performance over all completed iterations.



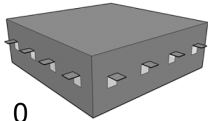
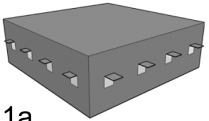
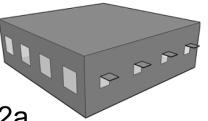
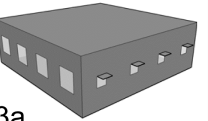
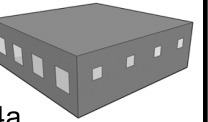
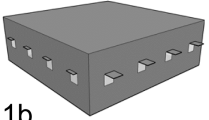
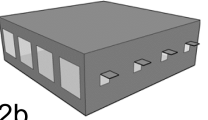
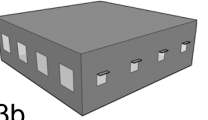
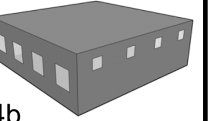
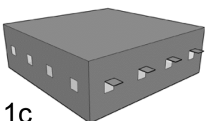
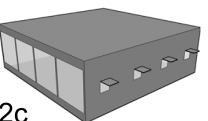
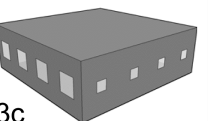
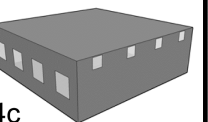
Original Model	Step 1: Shorten South Overhangs	Step 2: Increase South Window Area	Step 3: Shorten East Overhangs	Step 4: Move East Windows Up
 0	 1a	 2a	 3a	 4a
49.0%	57.4%	BEST: 94.9%	96.0%	BEST: 98.1%
	 1b	 2b	 3b	 4b
	69.6%	55.3%	96.5%	97.7%
	 1c	 2c	 3c	 4c
	BEST: 78.9%	24.6%	BEST: 96.7%	96.1%

Figure 8 The performance and designs of the first four design steps of an example problem. The performance goal considered is a wide illuminance range (described further as case study #1). The “perfect user” selections are 1c, 2a, 3c, and 4a.

It was not possible to select a “best” performing design from either the GA or the expert system for case studies involving multiple conflicting goals. In these cases, an approximate Pareto front was created by the multi-objective GA to demonstrate the range of possible designs and their performances for each of the conflicting goals. The designs

produced by the expert system were compared with those along the approximated Pareto front.

For all case studies presented in section 3.1, the “uniform window” scheme was selected. The behavior of the expert system for the “non-uniform window” scheme will be discussed in section 3.2.

3.1.2 Comparison Case Studies Results

This section presents five case studies that demonstrate the range of problems that the expert system can handle successfully. The authors also initially completed simpler studies in which single goals were considered with either minimum or maximum illuminance values or a maximum glare threshold. Although they are not presented here, in all simple case studies, the expert system was able to find a solution within 10 design iterations that met the performance goal over 100% of the sensor plane area and over all times of year.

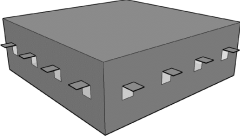
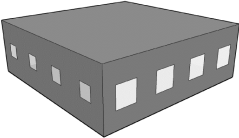
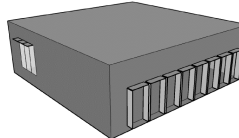
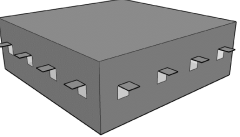
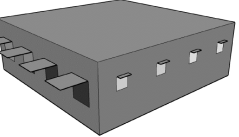
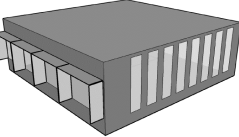
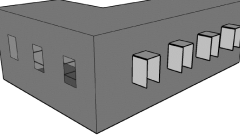
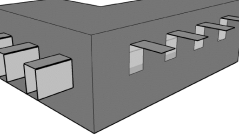
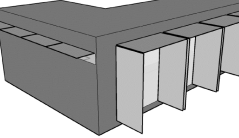
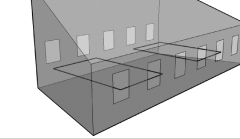
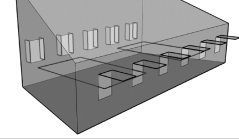
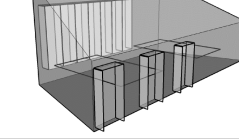
Performance Goal	Expert System Starter Design	Expert System Best Design	Micro-GA Best Design
Case Study #1 One Illuminance Goal: Wide Range	 49.0% In Range	 99.8% In Range	 99.9% In Range
Case Study #2 One Illuminance Goal: Narrow Range	 49.2% In Range	 94.4% In Range	 97.3% In Range
Case Study #3 Two Illuminance Goals: Sensors Parallel to Facades	 64.5% In Range	 96.1% In Range	 95.3% In Range
Case Study #4 Two Illuminance Goals: Sensors Perpendicular to Facades	 61.3% In Range	 82.6% In Range	 87.0% In Range

Figure 9 Comparison of best performing final designs from the expert system and micro-GA for case studies #1 through #4

3.1.2.1 Case Study #1: Wide Range Illuminance Goal

The first two case studies consider a simple box model with a single illuminance sensor plane located in the core zone and two external façades with windows oriented towards the east and south. The first case study considers a single performance goal with an illuminance range: 300 lux minimum preferred (100 lux accepted) and 1500 lux maximum preferred (2500 lux accepted). This is a relatively simple problem to solve, given that the range of acceptable illuminance values is fairly wide. For this case study, only the school schedule was considered (morning through mid-day, autumn through spring).

In this case study, the micro-GA was able to find a solution that was essentially “perfect” (99.9% in range) after 10 generations. The expert system was also able to find a near-perfect solution (99.8% in range) after 10 design iterations. The best performing designs for both algorithms are shown in Figure 9. Both final designs feature smaller windows on the south façade and larger windows on the east façade, and both designs have small or no shading devices on either façade.

3.1.2.2 Case Study #2: Narrow Range Illuminance Goal

In this case study, the same initial model as the previous case study was used with a narrower illuminance range as a performance goal: 300 lux minimum preferred (100 lux accepted) and 800 lux maximum preferred (1200 lux accepted). Because the illuminance range is stricter than the previous case study, the problem is more difficult to solve. Like the previous case study, a school schedule was considered for this problem.

In this case study, the micro-GA was able to find a design with excellent performance (97.3% in range, for the times and seasons considered) after 10 generations. The expert system was also able to find a design with very good performance (94.4% in range). The final designs produced by the two algorithms (Figure 9) both have large shading devices on the south facing windows; however, the east façades are visually very different. This difference may be the cause of the 3% difference in performance between the final designs found by the two systems.

3.1.2.3 Case Study #3: Two Illuminance Goals – Sensors Parallel to Façades

This case study considers an L-shaped space with two illuminance goals. The two façades of interest are oriented towards the south and west, and the two illuminance sensors are located parallel to these façades (Figure 7). The illuminance goals for each sensor are:

- South zone: 400 lux minimum preferred (200 lux accepted); No maximum.
- West zone: No minimum; 500 lux maximum preferred (800 lux accepted).

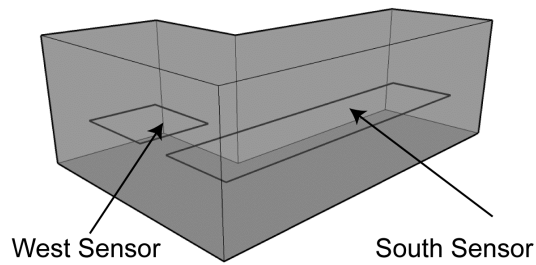


Figure 10 L-shaped initial massing model for case study #3 with two illuminance sensors indicated

Based on these goals, the known design solutions to this problem featured small, shaded windows on the west façade and larger windows on the south façade.

For this case study, the goals were considered non-conflicting and the total performance of each design was calculated as the average performance of both sensors. The expert system was able to find a design solution with an average of 96.1% in range. The micro-GA found a similarly good solution with an average performance of 95.3%. As expected, both “best” designs have either very small or highly shaded windows on the west façade with larger or less shaded windows on the south façade (Figure 9).

3.1.2.4 Case Study #4: Two Illuminance Goals – Sensors Perpendicular to Façades

The second non-conflicting goals case study considers a trapezoidal space with a sloped roof. The two façades of interest are oriented towards the south and north, and the two illuminance sensors are located perpendicular to these façades in the east and west ends of the space (Figure 10). In this case study, the height of the north façade is twice the height of the south façade. The illuminance goals for each sensor are:

- East zone: 200 lux minimum preferred (100 lux accepted); 800 lux maximum preferred (1200 lux accepted)
- West zone: 400 lux minimum preferred (200 lux accepted); No maximum.

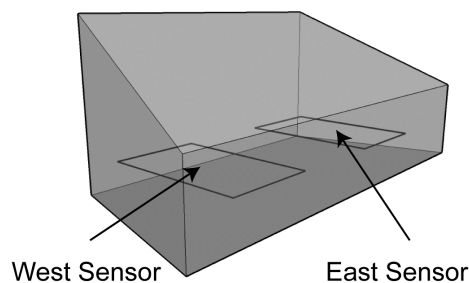


Figure 11 Trapezoidal initial massing model for case study #4 with two illuminance sensors indicated

As with the previous case study, total performance is considered as the average performance of the two illuminance goals. The micro-GA was able to find a solution with an average performance of 87.0% while the expert system's best design had an average performance of 82.6% (Figure 9). It is clear that both systems struggled with this particular case study, which indicates that the performance goals may have been somewhat conflicting. This case study represents the largest difference (4.4%) between performance found by the expert system and that found by the micro-GA.

3.1.2.5 Case Study #5: Conflicting Illuminance and Glare Goals

This case study is a conflicting goals scenario which features one illuminance goal with a desired range of high illuminance values and one glare goal. The goals in this case are conflicting because achieving the illuminance goal is likely to cause glare to increase for the views considered. This case study considers a Z-shaped floorplan, and the two façades of interest face east and west (Figure 12). Two illuminance sensor planes are located in the east and west zones and glare arrays are located within the same zones with views facing outwards.

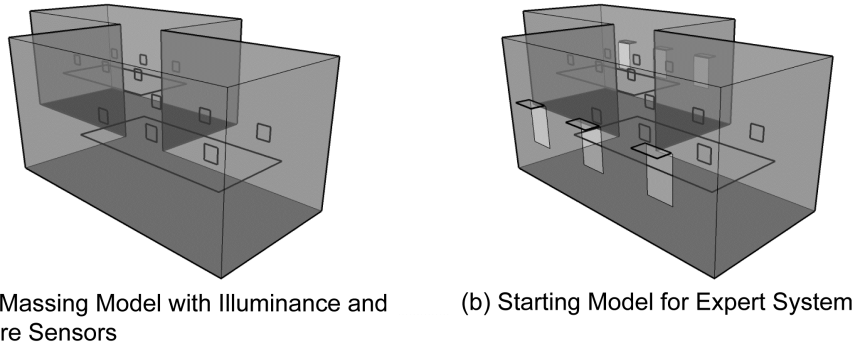


Figure 12 Initial Z-shaped massing model (a) and façade design (b) for case study #5 with illuminance and glare sensors shown.

The performance goals for the two sensor groups are:

- Illuminance: 200 lux minimum preferred (0 lux accepted); No maximum.
- Glare: Zero glare tolerance (only imperceptible glare allowed).

This case study had an additional constraint that all façades must be uniform and that all façades must be identical to ensure that the performance goals would be conflicting.

Because there cannot be a single “best” solution to a problem with conflicting goals for this case study, an approximated Pareto front was generated using a multi-objective micro-GA [16]. The approximated Pareto front demonstrates the range of possible solutions that are considered non-dominated. By examining the set of all non-dominated solutions, one can begin to understand the relationship between the two conflicting performance goals.

To compare the results of the expert system to those generated by the multi-objective micro-GA, the expert system was run three different times, each for five design iterations,

with a different sensor priority given for each of the three runs. When all the designs generated by the expert system over the three runs are compared to those generated by the micro-GA over 50 generations (Figure 13), it is clear that the expert system designs cover a wide area within the solution space and offer a way of approximating the Pareto front using fewer total simulations than those required by the micro-GA.

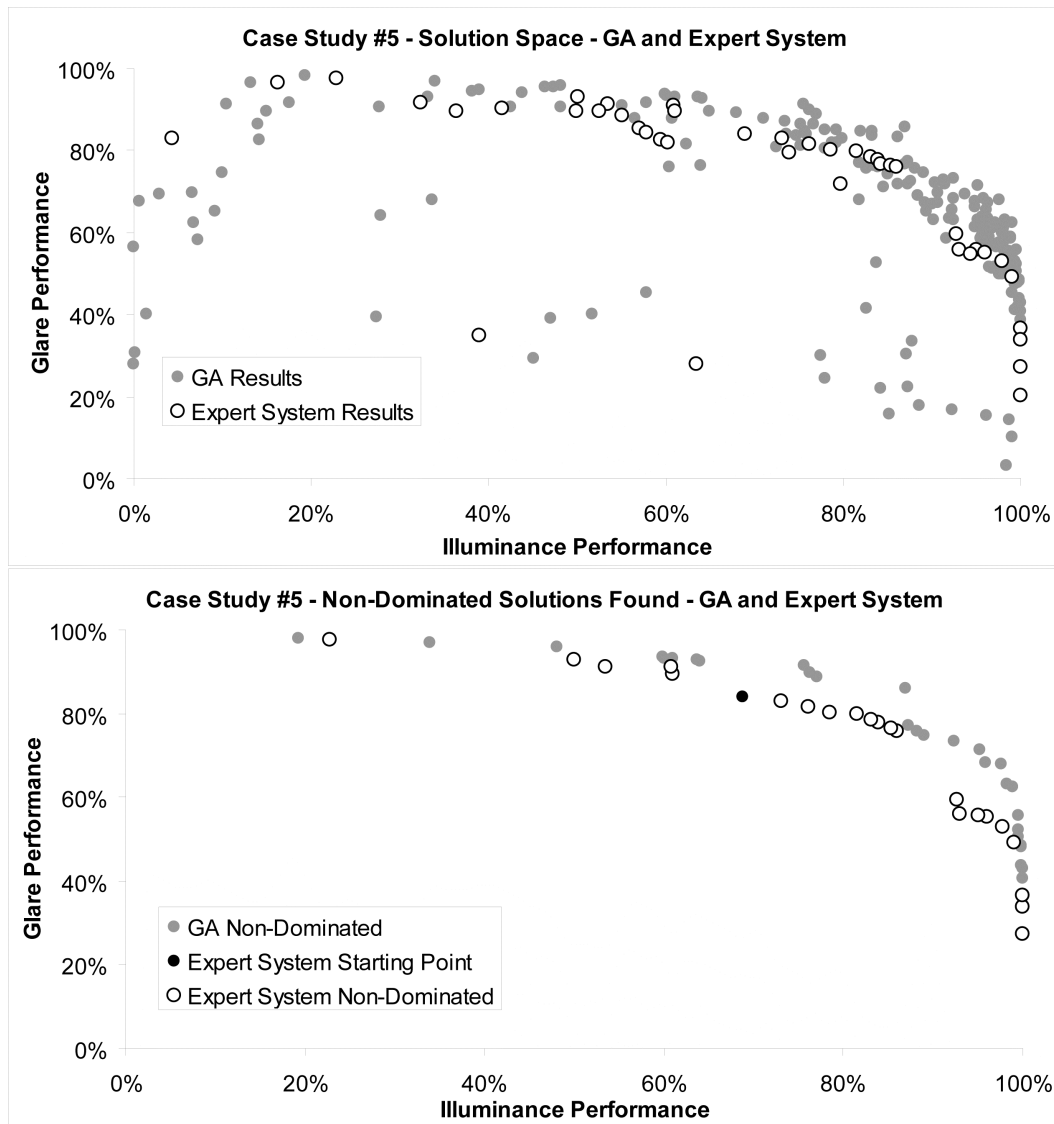


Figure 13 Case study #5 - Conflicting illuminance and glare goals: Performance for the expert system for three different goal priority scenarios over the entire solution space (upper) and over the approximated Pareto front (lower).

Although the expert system does not generate a Pareto front itself, it is interesting to compare three designs generated by each algorithm: the design with the best average performance, the design with the best illuminance sensor performance, and the design with the best glare sensor performance (Figure 14). In this case study, the micro-GA was able to find a design with an average performance that is over 5% better than the design found by the expert system, and in general, it is clear that the expert system designs

tended to have slightly lower glare performance than the micro-GA designs in the middle area of the Pareto front. However, the expert system is still able to effectively provide the user with a rough approximation of the Pareto front and a set of designs that explores the trade-offs between illuminance and glare performance.

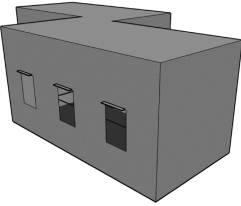
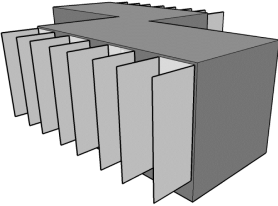
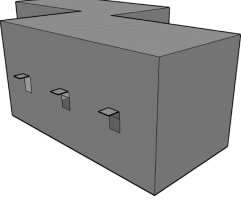
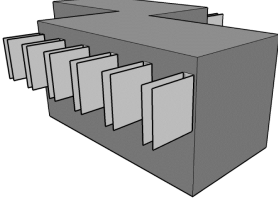
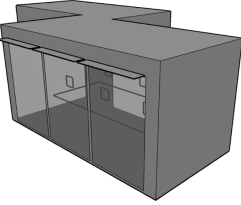
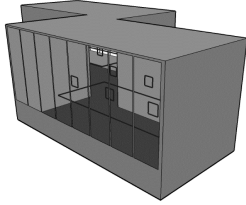
Case	Created by Expert System	Generated by Micro-GA
Best Average Performance		
	Average: 80.9% Glare: 75.8% Illuminance: 86.0%	Average: 86.4% Glare: 85.5% Illuminance: 87.0%
Best Glare Sensor Performance		
	Average: 60.3% Glare: 97.7% Illuminance: 22.8%	Average: 58.7% Glare: 98.1% Illuminance: 19.3%
Best Illuminance Sensor Performance		
	Average: 63.6% Glare: 27.2% Illuminance: 100.0%	Average: 67.2% Glare: 34.5% Illuminance: 100.0%

Figure 13 Case study #5 - Conflicting illuminance and glare goals: Comparison of designs for best average, glare, and illuminance sensor performance for the expert system and the micro-GA./

3.2 Façade Constraint Case Studies

While the previous set of case studies was able to demonstrate that the expert system can indeed produce designs that are comparable to those produced by a micro-GA, the behavior and performance of the expert system is also dependent on several variables that do not affect the micro-GA. One important difference between the micro-GA and the expert system is that the micro-GA generates its own designs while the expert system

begins with an initial design and suggests changes to be made to that specific design based on its current performance. The best design produced by the expert system is thus highly dependent on the initial design given to the system.

The expert system also allows the user to select a uniformity scheme for the windows in his or her design. In the micro-GA comparison studies, both the micro-GA and the expert system designs were constrained to have uniform façades, which meant that all windows on a single façade had the same characteristics. However, the expert system includes the option of having non-uniform façades. Selecting this option would allow the system to make changes to individual windows on a façade instead of all of them at once. For certain types of design scenarios, selection of the non-uniform window option will result in greater performance improvement than the uniform window option.

Two brief case studies examine the effects of the initial façade design and the window uniformity scheme on the overall improvement found by the expert system.

3.2.1 Effect of Initial Façade Design

To examine the relationship between the performance of the expert system and the initial façade design, the problems in the micro-GA case studies #1 and #2 (sections 3.1.2.1 and 3.1.2.2) are considered: a simple box model with an illuminance sensor in the core zone, external façades on the east and south, and an illuminance range as a performance goal. The two case studies differ as the performance goal for one is a wider illuminance goal range than the other, which is therefore an easier problem to solve. These case studies enable a comparison of the expert system behavior for different façade types on two different levels of goal difficulty.

In the original case studies presented, the expert system process began with a relatively generic façade design with mediocre performance (around 50%). In this study, four different starting façades are shown in Figure 15 and have varying levels of specificity: the first is the generic façade with square windows, the second has slightly more elongated windows, the third has extremely elongated windows, and the fourth has elongated windows clustered towards one end of each façade.

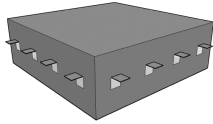
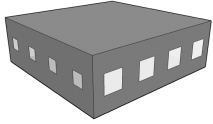
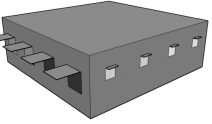
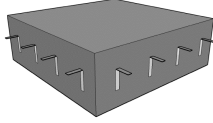
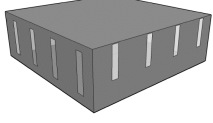
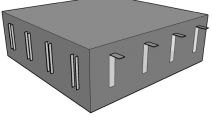
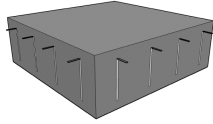
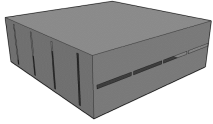
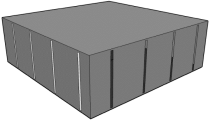
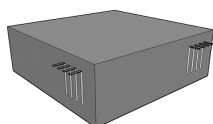
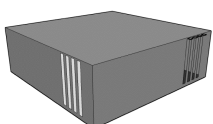
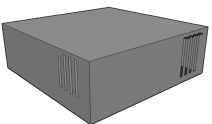
Facade Type	Starter Design	Best Design: Wide Range	Best Design: Narrow Range
Generic			
	Wide: 49.0% Narrow: 49.2%	99.8% In Range	94.4% In Range
Somewhat Stylized			
	Wide: 49.1% Narrow: 49.2%	94.5% In Range	92.3% In Range
More Stylized			
	Wide: 47.8% Narrow: 47.3%	95.1% In Range	93.4% In Range
Most Stylized			
	Wide: 52.0% Narrow: 51.6%	98.3% In Range	88.4% In Range

Figure 15 Starter and best designs for four levels of façade specificity and two levels of goal ranges (wide and narrow)

In this study, the expert system process was run for each of the four initial façade types and for each of the two illuminance goal ranges. The expert system was run for 10 design iterations in all cases, and the “uniform façade” scheme was selected. The best performing final designs for all cases are shown in Figure 15.

For both cases, it is clear that the starting design clearly influences the aesthetic of the final best performing design; however, in all cases, good solutions were found. The wide-range goal case study was more successful, with performances ranging from 94.5% to 99.8%. This result was expected as this goal is easier to meet. For the narrow range goal case, solutions with performance ranging from 88.4% to 94.4% were found.

3.2.2 Effect of Selected Window Uniformity Scheme

In addition to being heavily influenced by the initial façade design, the expert system’s search process is also dependent on the window uniformity scheme selected by the user at the beginning of the process. In this section, the models from case studies #3 and #4 from the micro-GA comparison studies were considered (sections 3.1.2.3 and 3.1.2.4), once with the uniformity of the façade maintained and once with non-uniform façades allowed.

It was hypothesized that the uniformity of the façade would be more influential on designs with more than one goal than for single-goal scenarios. These two design problems each have two illuminance sensor planes with different performance goals, but they are considered non-conflicting goals because reasonable solutions exist which meet both goals at once. For the L-shaped room case study, the known good solutions featured small windows with shading devices on the west façade and larger windows on the south façade. For the trapezoidal case study, the known good solutions feature windows clustered towards the west end of both façades. The best performing designs found by the expert system for both uniform and non-uniform façades for both case studies are shown in Figure 16.

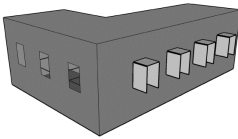
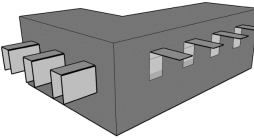
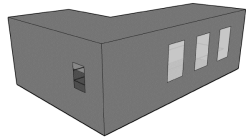
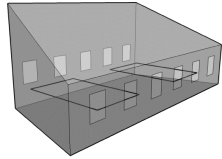
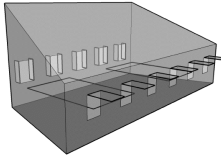
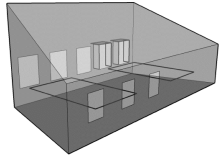
Performance Goal	Starter Design	Uniform Facade Best Design	Non-Uniform Facade Best Design
Two Illuminance Goals: Sensors Parallel to Facades			
	64.5% In Range	96.1% In Range	97.5% In Range
Two Illuminance Goals: Sensors Perpendicular to Facades			
	61.3% In Range	82.6% In Range	96.4% In Range

Figure 16 Comparison of best performing final designs from the expert system for L-shaped and trapezoidal models (from case studies #6 and #7) with two different uniformity schemes

Figure 16 indicates that the non-uniform window scheme produces significantly better results for the trapezoidal case study, where the sensor planes are located perpendicular to the façades of interest. The non-uniform window scheme allows the expert system to target the two illuminance sensors individually by making different changes to the windows that are located closest to each one instead of making the same design change to all windows. The final design for the non-uniform scheme still resembles the initial façade design, but the façades have each been divided into two, based on the locations of the two sensors. This final design has an average performance of 96.4%, which is 13.8% better than the performance of the uniform façade design. In the L-shaped case study,

where the sensor planes are located parallel to the façades of interest, the non-uniform façade scheme produced slightly better performance, but the final best designs for both schemes are within 1.1% of each other. This set of case studies demonstrates that the use of the non-uniform window scheme can produce dramatically better results for certain types of designs.

4. Discussion

Based on the results presented in section 3, the expert system was found to be successful at making design decisions that improved the daylighting performance of five case study designs. In these case studies, the performances of designs using the expert system were compared to baseline examples generated by a micro-genetic algorithm (micro-GA). The purpose of the comparison studies was to evaluate the performance of the expert system relative to a known optimization algorithm which could be relied upon to consistently generate designs with very good, if not globally optimal, performance. The results of these case studies indicated that the expert system was successful at improving the performance of designs for a variety of initial conditions and performance goal scenarios. In some situations, the micro-GA was able to find designs which performed slightly better than those found using the expert system, but this difference in performance was small (4.4% at most for all case studies considered) and acceptable given the fact that the expert system was designed with user interactivity in mind, while the micro-GA was not.

Two additional short studies were completed which investigated the effect of initial façade conditions and the effect of user-selected window uniformity constraints on the performance of the expert system. In the first study, it was found that although the initial façade design may affect the expert system performance, the system was still able to improve performance for even highly designed façades. For more stylized initial façades, it was found that the final improved designs were similar in appearance to the original designs, which demonstrates that the expert system preserves the original design intent. In the second study, it was found that the window uniformity scheme selected by a user can have a significant effect for certain types of model geometries. For models in which the sensor planes are located perpendicular to the façades of interest, the non-uniform window scheme selection was found to improve expert system performance (by over 10% in the case study considered).

The expert system developed for this paper was a prototype tool which has several limitations. Due to the structure of the tool, the expert system requires the use of a pre-computed database (“knowledge-base”) for its decision-making logic. Although the system presented in this paper used a knowledge-base specifically for Boston, the addition of new climates or locations would be straightforward, requiring only the creation of new climate-specific knowledge bases based on the method described in [18]. However, the simulations required to create such knowledge-bases are time-consuming and would likely prove too complex for a casual user. A more robust version of the expert system would feature a selection of pre-computed knowledge-bases available for a variety of locations. Alternatively, more climates could be considered using a more

generic meta-database, which could potentially be designed to be applicable to multiple locations using weight factors based on climate and latitude.

The current expert system was also limited in its use of geometrical forms. Only designs with orthogonal components can be considered by the expert system, and the number of possible façade design changes it can suggest was limited to those which could be implemented using existing functionality in the SketchUp Ruby API. These geometrical limitations constrained the number and type of designs that could be tested in section 3. Given the wide range of complex forms that designers can now create using digital tools, these limitations also restrict the potential for the expert system to be used in actual design scenarios. One partial solution is to expand the system to include a larger set of design changes and geometries, which would require an expanded knowledge base. Such a database could be populated using a method similar to the current knowledge base, with a larger set of variables. Because the system reads the knowledge base data from a text file kept separate from the coded logic, an expanded knowledge base could be added into the current system with only a small amount of editing to the code, mostly to accommodate the addition of new automated design changes. The addition of a significantly larger knowledge base could potentially increase the time required for the expert system to make decisions; however, such an increase would likely be negligible compared to the time necessary for simulations. The expansion of the system to include more varied geometrical forms would require integration of the expert system into a more flexible 3d modeling environment, for example a NURBS-based tool such as Rhinoceros.

5. Conclusions

This paper presents a new user-interactive expert system approach which enables architects to consider daylighting goals in the early design stages by engaging them in a performance-driven design exploration process. One of the goals of this research was to introduce a new method for performance-driven design that allows a user to receive design suggestions that are specific to his or her original model and performance criteria. This goal required that the expert system be a highly flexible system that can produce positive results for a wide variety of possible inputs. The results of the case studies indicate that the expert system may find designs that perform similarly to those generated by an optimization algorithm; additionally, it may retain some of the qualities of the user's original design, such as stylized façades. Based on these results, a potential user can have confidence that the design changes suggested by the system will improve the performance of his or her initial design if a number of design iterations are completed. If a true optimal design is not required, the expert system may be used in lieu of a traditional optimization method to find design with improved performance. However, as the expert system relies on an entirely different type of algorithm, it may also be used as a valuable complement to the optimization process, providing feedback in the form of design suggestions that may inform the purely performance-driven results of optimization.

While the current version of the tool is limited by the geometries, locations, and performance metrics that it can consider, the expert system has a flexible structure which

could act as a framework for future expansion in areas that would enable the system to become more viable for use in actual design practice. Such an expansion could include additional locations, geometries, and design suggestions, as discussed in section 4. Additionally, while the current system considers only daylighting performance, it could be possible to expand the system to consider performance in other domains by considering solar thermal gains or building energy use. The solar thermal gains metric can already be calculated using the LSV engine, while building energy use could be calculated using an existing simulation engine from within SketchUp, such as EnergyPlus [23]. The addition of new metrics would require a substantial expansion of the current system, including the development of new knowledge bases and new fuzzy logic rules to work with the additional information. More research is necessary to assess the feasibility of such a scheme.

In addition to the case studies presented in this paper, the expert system has also been tested by a group of designers who were asked to complete a design task with the system and to evaluate their experiences using the tool. The results of these user studies were positive and will be presented in a future paper.

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