Generating Alternative Engineering Designs by Integrating Desktop VR with Genetic Algorithms

Magesh Chandramouli, Gary Bertoline, Patrick Connolly
Department of Computer Graphics Technology
Purdue University, West Lafayette, IN 47907

Abstract

This study proposes an innovative solution to the problem of multiobjective engineering design optimization by integrating desktop VR with genetic computing. Although, this study considers the case of construction design as an example to illustrate the framework, this method can very much be extended to other engineering design problems as well. The proposed framework generates optimal solutions for the problem of construction design, which is becoming an increasingly complex problem due to the multitude of factors involved in the process. This study places special emphasis on the modeling of the scenes within the virtual world from the design perspective. Even though genetic algorithms (GA) have been used by professionals in diverse disciplines to optimize conflicting objectives, these provide the end user with a pool of solutions rather than a unique solution that can be implemented. Hence, this study proposes a desktop VR framework that serves as a visualization tool to aid decision makers to better evaluate the alternative solutions from the Pareto set resulting from the GA process. Modeling alternative scenarios is formulated as an optimization problem wherein design configurations are generated using genetic algorithms. With the goal of sustainable and non-destructive construction design and planning, the algorithm is intended for multiple objectives. The study also presents an innovative perspective on this whole process by presenting the qualitative evaluation of the scene based on human evaluation and incorporating changes. The results demonstrate the robustness of the GA framework and also substantiate the utility of the virtual scenarios.

INTRODUCTION

Invariably, today's complex design problems demand coordinated optimization of multiple objectives. The solution is to resourcefully negotiate the different objectives resulting in a judicious compromise. Genetic algorithm (GA) based multiobjective optimization techniques have been successfully applied to a wide range of disciplines in the recent past. Genetic algorithms are heuristic search procedures employed in finding solutions for multiobjective optimization problems. The GA process generates a group of optimal solutions for the particular multiobjective optimization problem, which is known as the Pareto set, with plans that represent a meticulous trade-off (Stew-art, Janssen, & van Herwijnen, 2004). For any design optimization, the decision makers are looking for a single satisfactory solution that can finally be implemented. When using genetic algorithms (Goldberg, 1989) for multiobjective design optimization, it is very important to carefully scrutinize the differences among the candidate solutions to obtain a better knowledge of the basic processes and the satisfaction of objectives. The process of choosing one single solution over others entails exhaustive domain knowledge. Typically, many GA-based design optimization procedures make the final choice of the solution (from the Pareto set) based on some 'higher level information' (Seixas, Nunes, Louren, Lobo, & Condado, 2005). However, when it comes to design and planning, it is

not possible to implement all the conflicting solutions in the Pareto set (resulting from the GA process). Hence, we offer a virtual reality based visualization to explore and study the alternative solutions. Visualization, as defined by Spence (2007) as the ability "to form a mental model or mental image of something." (p. 5), is a very handy cognitive ability that holds immense potential in the domain of planning and designing (Tufte, 1990). Spence (2007) noted that advances in computer technology have led to a huge increase in the application of information visualization over the past two decades. Visualization models have been built in research disciplines including medicine, education, mining, GIS (Geographical Information Systems), and various other domains to facilitate information comprehension and analysis. The power of visualization models lie in their ability to present data in a form that allows the viewer to 'see' the information in a way more easily interpreted and understood. Elements that need to be considered in construction design and planning include the floor space, structural requirements of the proposed construction, recreational and public amenities (as required), aesthetic concerns, and so on. Providing satisfactory solutions in the face of conflicting demands by multiple stakeholders is a daunting task. Therefore, the proposed framework offers interactive 3D scene visualization to facilitate comparing the alternatives. The GA in this study includes a well-planned selected set of objectives that are explicitly conflicting: maximization of shopping space, maximization of recreational space, and maximization of public service space. Inherently, these three objectives are conflicting in nature as an increase in one space will lead to a decrease in one or both of the others.

The outline for this paper is as follows: Section 2 discusses the process of multiobjective optimization and the various approaches for multiobjective design optimization. Section 3 delineates the GA methodology employed in this study and explicates the research framework and the components. Section 4 elucidates the shopping mall plans and the adaptation of the GA for the floor plans. Section 5 explains the Desktop VR rendering of the plans. Section 6 provides the discussion followed

by section 7 that briefly discusses qualitative scene analysis based on human evaluation and subsequently modifying the scene accordingly. Finally, Section 8 presents the conclusion of the study.

MULTIOBJECTIVE OPTIMIZATION IN ENGINEERING DESIGN PROBLEMS

Notwithstanding the remarkable advancements made within the realm of engineering design, owing to the ever-increasing number of factors in any major project, the design exercise has become a complicated process and satisfying all objectives seems to be a daunting and sometimes impossible task. Every design process today is inherently driven by the needs of the consumer and/or the stakeholders and there should be a means to verify if the proposed plan will meet all the demands. It amounts to a colossal waste of time, effort, and money to construct a project and finally realize that it falls short of some objectives initially set out. Consequently, considerable care has to be exercised during the planning and designing phases. Typical design problems consist of a predefined set of decision variables and a particular number (n) of objective functions that need to be maximized or minimized under a given set of constraints. In order for a plan to be considered part of the Pareto set, no other plan, which is superior in all objectives, should be found. In other words, a plan may outdo the Pareto plan in one objective and a different plan may be better in another objective; however, a 'single plan' does not outperform a Pareto plan in all the objectives. From the above discussion it can be seen that plans that do not belong to the Pareto set (non-Pareto plans) are 'dominated', because a Pareto plan that is better (or that which dominates) already exists.

Multiobjective genetic algorithms (MOGA), a family of heuristic methods, overcome the limitations of traditional methods because it is capable of solving the non-linear, non-additive optimization problems without reformulating the problems. With these merits, MOGA has been adopted in a large number of design and planning research projects (Stewart et al., 2004; Balling, Powell, & Saito, 2004). However, because MOGA usually

retrieves a large number of optimal design plans, new techniques are needed in order to facilitate spatial decision making, among which visualization plays an important role. In particular, to visually plot the candidate solutions of the design space is an intuitive way to visualize these optimal alternatives.

METHODOLOGY

The study area considered here is the floor space (400 cells) for a shopping and residential mall that is usually divided into zones (various spaces based on usage). These zones are allowed to assume different values. The genetic framework for the region is represented by a 'gene' for every changeable zone. In this study, we use an integer based genetic representation, i.e. each gene is an integer that can assume any value from among the various designs considered in the study. In this example, the zones are coded as follows: Public Service Space is assigned a FL_CODE of 0, Food Court 1, Parking Spaces 2 Convention/Conference area 3, Recreational spaces 4, Public Service Spaces 5, Commercial Space – Supermarkets 6, Commercial Space – IT offices 7, Commercial Space – Other Shopping Spaces 8, Control and Reserved Spaces 9. Therefore, each zone is plotted or mapped to an integer within the range of 0-9, and the integer values of all such zones are linked together, resulting in an integer string (Chandramouli, Huang, & Xue, 2009).

In the beginning (first generation), a random value is assigned by the GA to each gene. The generation size is chosen as 100, corresponding to 100 floor plans. Then, each plan is scrutinized with respect to the three objectives and three constraints. Plans that meet the constraints are deemed as practicable ones. The goal is to produce a land-use map that will ensure maximum values of shopping space, recreational space, and public service space. As the design variables can assume any of 10 integer values, the total set of possible plans is as big as 10n, where n is the number of cells (400). This signifies an enormously discrete search space. Probably only a tool like GA that is robust and efficient is capable of performing multiobjective

optimization in such a large search space.

Considerations in GA Formulation

Adequate care has to be taken in the process of formulating the GA. Clear representation of the problem is inevitable for an effective solution. Just as alternative solutions are possible, alternative representations are also possible. When considering floor plans, it is possible to represent the problem in the form of raster or vector spaces. In this case, cells of equal dimensions have been chosen. In other words, the study area has been divided into a grid of rasters. However, it is possible to characterize the same problem using a vector representation similar to that used in Geographical Information Systems (GIS) (This concept is later illustrated using Figure 3a and Figure 3b). In GIS, vectors or polygons are used to denote land parcels whose dimensions are specified using attributes. Also, even when choosing to use a raster-based representation, various options are available. The size of the individual cells is an important factor to be considered. The area can be divided into 20 x 20 cells or 200 x 200 cells or even 2000 x 2000 cells. Several considerations affect this decision including the computing power available for the GA process.

GA Framework

GAs typically consist of the following steps:
*   Selection process wherein the individuals for the next generation are chosen
*   Manipulation, wherein recombination and mutation are performed using genetic operators

In this study, integer based representation, a common method of encoding used in GAs, has been implemented. The genetic framework for the region is represented by a gene for every changeable zone (Figure 1).

Figure 1. A chromosome structure with integer representation

We use integers because integers are simple and straightforward from the computational perspective. The generation size is chosen as 100, resulting in 100 floor plans at the end of the execution of the first generation. An initial generation is created by a process of random generation in the presence of constraints and the iterations are repeated until a feasible set is obtained. 'Feasible set' refers to plans that satisfy the constraints imposed. During iteration, the plans in a generation are checked individually for satisfaction of the minimum requirements/constraints and those that satisfy these requirements are added to the feasible set and the others are discarded. The procedure is repeated until the initial generation with 100 chromosomes (floor plans) is obtained (Figure 2). After the initial generation is obtained, the selection, recombination, and mutation processes are performed to create the subsequent generation.
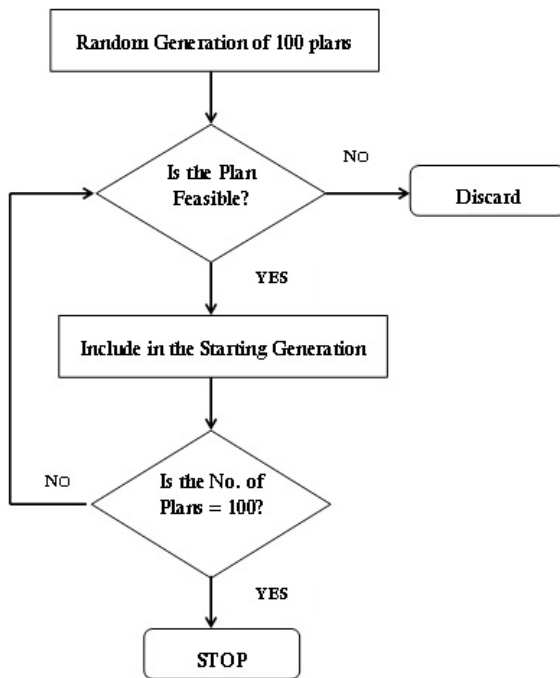
Figure 2. Generation of the 'feasible set'

Selection and Variation

As stated earlier, the GA process consists of two very fundamental operations, namely selection and variation. The selection process is the step whereby the individuals that are 'fit enough' to be passed on to the next generations are chosen. Typically, this process is biased by the fitness of the individuals in such a way that individuals with higher fitness have a great probability to make it to the subsequent generation. The selection process can be stochastic or deterministic; the basic objective is to eliminate the poor quality individuals from the population set. The value of an individual member of the population with respect to the optimization process is represented by a scalar quantity known as 'fitness'. The fitness value is calculated based on the objective functions and constraints. After calculating the fitness values of every individual in the generation, those members with higher fitness values are selected for the subsequent generation. However, not all the members from the present population can be selected for the next generation. This proportion is called the rate of selection or selection rate. For instance, if the selection rate is .2, then out of a population of 100, 20 individuals will be selected for the next generation. Likewise, if n = 100, and x = 0.4, then 40 individuals are obtained by selection and the remaining 60 are generated by the processes of recombination and mutation. One vital consideration during this step is the choice of the number of chromosomes to retain. If there is a considerable number of poor quality chromosomes in the present population, retaining a large number of these chromosomes for the next generation will negatively affect the overall fitness of the generation. On the other hand, if only a minimal number of chromosomes are retained from the present generation to the next generation, this will restrict the number of genes available in the offspring. This step mimics the natural selection process. In the process used in this study, chromosomes with a fitness value below the threshold limit are not considered for the next generation.

Subsequently, recombination, the process of merging the genetic information from two parent chromosomes follows. In the recombination step, a predetermined number of parents are selected and are recombined using crossover operations to create children. In order that the process remains stochastic, a probability rate known as crossover probability is used along with the crossover operator. The crossover point is where the swapping of

genes occurs. This point is chosen randomly and it lies between the first and last genes of the chromosomes. At first, one of the two members of the mating pair, called Parent1 provides the genes to the left of the crossover point to the Offspring1 and the second member of the mating pair, Parent2 provides the genes to the right of the crossover point to the Offspring1. Thus, the Offspring1 now contains material from both the parents. Similarly, the second offspring is generated by combining material from Parent1 and Parent2. The genes to the right of the crossover point from Parent1 and that to the left of the crossover point from Parent2 are combined to produce Offspring2. Once the recombination step is over and the crossover operations are complete the generation is full with its complete population of chromosomes. At this stage, random mutations are introduced in the population. Mutation helps the GA process in two ways:

1. Mutation helps prevent premature convergence
2. Mutation aids establishing new traits not present in the original population

Subsequent Generations and Convergence

After the mutation step is completed, the resulting generation is ready for the iterative process. The steps starting from fitness calculation are re-run for the individual chromosomes of the new generation and this generation undergoes the steps of selection, recombination, and mutation as before until the subsequent generation is obtained. The iterative process of the subsequent generations depends on

- Whether specific search criteria have been satisfied or
- Whether a specific number of iterations have been surpassed

Objective Functions and Constraints

In this study, three objectives were considered, which ensure that:

1. The building can accommodate more commercial establishments

2. The recreational spaces are increased,
3. The residents and the shopper get more space for public amenities

Genetic algorithms typically consist of functions or objectives that are to be maximized or minimized during the process of optimization. In this study we wanted to have objectives that are directly and intensely conflicting in terms of area. The first objective was meant to increase the shopping space as typically stakeholders would be interested in enhanced commercial value for higher return on investments. Three index values: CommVal, Recval, and PubVal, are used as objective measures. The objectives are to maximize the commercial value, recreational value, and the amount of public service space. Among the 10 floor space types seen in this study, one particular floor space type needs special consideration. These are the control and reserved spaces, which are set aside for special purposes. Different sets of uses and regulations govern the use of such floor space types and changes, if any, to such areas involve considerable administrative brainstorming. Hence, the floor space types categorized as control and reserved will continue to remain unchanged by the GA process.

The three indices are calculated as follows for the 100 plans in a generation:

for i = 1:100
$Pub_{Val}(i,1) = (Area_{Rec}(i,1))/Sum_{Area}$;
End
Where,
Pub_{Val} = Index for measuring recreational value of a plan,
$Area_{Rec}(i,1)$=Area for recreational spaces in Plan i. &
Sum_{Area} = Total area of all the 400 cells

Similarly, the index values CommVal and PubVal are calculated. The following constraints are imposed on GA:Floor Spaces designated as Emergency Exits and those reserved for Safety purposes are not to be changed, Spaces designated as parking are not to be changed and Specific floor spaces with residential structures are not be changed. In order to ensure these constraints are met, a select-

ed number of cells from among the 400 cells are not allowed to change during the GA process.

Fitness Evaluation

After considering several fitness evaluation procedures, we find the Maximin function (Balling, Taber, Brown, & Day, 1999; Balling et al., 2004) to be very appropriate for GA studies involving problems involving category allocation for floor plans as seen in figure 3.

Val is the current value of corresponding objective, Val_{min} is the least value of all Val values of the plans in the current generation and
Val_{max} is the highest value of all Val values of the plans in the current generation.

Shown above is the normalization of the objectives using a simple and straightforward procedure that involves scaling. Normalization involves finding the maximum as well as the minimum values for each objective for a set of plans in a generation and then re-scaling using the following formula. The number of objectives is 3 in this study. The normalized objectives scores are given using a simple and straightforward technique of linear interpolation. Thus, considering the three objectives concerning Sustainability value of a plan, Economic value, and Recreation value, the normalized scores can be obtained as described above. The plans need to be compared with other plans in the generation to find the fit ones in the generation. As mentioned earlier, for measuring the fitness of the plans, the Maximin fitness function (Balling et al., 1999) is used. The fitness of each plan in a generation is calculated relative to that of the other plans in the same generation. The greater the CommVal, RecVal, and PubVal of a plan, the

higher will be the fitness of that plan in comparison with the other plans of the generation. Considering two plans Planj and Plani, Planj is superior to Plani if the indices CommVal, RecVal, and PubVal of Planj are all greater than the corresponding indices of Plani. Planj is superior to Plani if it exceeds it in all the three objectives. if the minimum of the above three differences is greater than 0, then Planj is superior to Plani.. Each plan in a generation must be compared with all the other plans in the generation. If it is to be found whether a Plani is dominated or not, it is compared with all other plans using the aforementioned principle. The fitness of the ith plan is obtained as follows in figure 4 (Balling et al., 1999):

Where,
    Range1 = CommValmax – CommValmin
    Range2 = RecValmax – RecValmin
    Range3 = PubValmax – PubValmin

Range1, Range2, and Range3 represent the scaling factors for the three objectives, for all the plans in a particular generation. However, it should be noted that this value has to be computed during each iteration for every single generation so the maximum and minimum values of each objective varies during each generation. Based on the fitness formula described above, it is possible to identify the Pareto-optimal plans from the fitness values obtained.

GA Implementation

The GA is implemented with the objective of searching and finding a set of plans for the community, which meet the constraints imposed on the GA while maximizing the objectives. Plans that satisfy the constraints are called 'feasible plans'.

$$Plan_j - Plan_i = \frac{Val_j - Val_{min}}{Val_{max} - Val_{min}} - \frac{Val_i - Val_{min}}{Val_{max} - Val_{min}} = \frac{Val_j - Val_i}{Val_{max} - Val_{min}}$$

Figure 3. Maximum function

$$f_i = \left(1 - max_{j \neq i}\left(min\left(\frac{CommVal_j - CommVal_i}{Range_1} \frac{RecVal_j - RecVal_i}{Range_2} \frac{PubVal_j - PubVal_i}{Range_3}\right)\right)\right)^{p}$$

Figure 4. Fitness formula

The final plans obtained from the GA must be Pareto-optimal with respect to the multiple objectives. Pareto-optimal plans are both 'feasible' and non-dominated. The word non-dominated implies that no other feasible plan in the generation is better than this plan in all objectives. In order to ensure that only plans that satisfy the constraints are included in the very first generation, randomly generated plans are scrutinized to check if they satisfy the aforementioned constraints. Only plans that satisfy the constraints are selected and included in the starting generation. This process is repeated until the starting generation has 100 plans, all of which satisfy the constraints (Table 1). From the starting generation, the second generation is constructed using the GA methodology. The third is generated from the second, the fourth from the third and so on for a total of 100 iterations at the end of which a generation with 100 final, feasible plans results. After mating, mutation is performed to introduce qualities that are not originally present in the parent population. Mutation involves randomly changing a selected number of genes in specific chromosomes obtained from the earlier process. In this study, the mutation probability is chosen as .05. Mutation is typically applied to the offspring generated from the earlier step, subject to the mutation probability. A random number between 0 and 1 is generated for each gene in the two offspring. If the random number is less than

the above probability of mutation (.05), then the integer value of the gene is changed to another random value between 0 and 9. The above processes cumulatively represent the complete process of creating a new generation from an earlier generation. This constitutes one sequence of iteration. The whole GA process involves 100 iterations at the end of which the Pareto set containing the Pareto-optimal plans is obtained.

The fitness values of the individual plans in the generation are calculated using the fitness formula described earlier Plans with higher fitness values have higher Pareto-optimality and hence are more 'fit' than the rest of the plans in the generation (the p value chosen here is 15 , Balling et al., 1999, 2004). The plans altogether constitute the Pareto set. Plans belonging to the Pareto set are called non-dominated plans. This is because no other plan exceeds the Pareto plan in all the objectives. A plan may outdo the Pareto plan in one objective and yet another plan may outperform the Pareto plan in another objective; however, no single plan surpasses the Pareto plan in all the objectives. The Pareto set is devoid of the influence of the relative significance of the various objectives. Hence, plans not belonging to the Pareto set are called dominated plans since Pareto plans that surpass these plans have been found. Pareto plans significantly aid the process of decision-making as planners and

---

Part I. Feasible Set Generation

1. Generate Random Population
2. Check for Constraint Satisfaction
3. Include in Feasible set Upon Satisfying Constraints
4. Repeat Steps 1-3 Till Population Reaches 100
5. Calculate Fitness of Feasible Set(Part II Steps 6-0)
6. Sort
7. Use Sorted Generation as Starting Generation

Part II. GA-Main Loop

1. Initiate Generation Number to 1
2. Select Top 10 Plans from Previous Generation
3. Use Tournament Selection to Select Offspring
4. Perform Mutation
5. Repeat Steps 3and 4 to Get 100 Chromosomes

6. Initialize Indices Matrix for Plans in a Generation
7. Get $Comm_{Val}$, Rec_{Val}, Pub_{Val} for 100 Plans
8. Compute Fitness Values
9. Sort plans based on Fitness
10. Set sorted generation as current generation
11. Repeat steps 1-11 for 100 Generations

Part III. VR-Visualization

1. Select Pareto-plans from Final Generation
2. Identify Scene Elements to Compose Virtual Envt.
3. Render the 3D Elements to Generate Virtual Scene
4. Evaluate Plans & Select 1 Plan for Implementation

Table 1. Algorithm for GA Based 3D Visualization

administrators need not sift through hundreds of thousands of plans; but, they can merely search the Pareto set to find an optimal plan. However, there is still one shortcoming. Decision makers are still confronted with a set of plans from which they have to choose one plan. This process cannot be automated as now the relative significance of the various objectives based on the ultimate development goals should be considered. This is a prototype study that proposes the use of VR-based representation to visualize two plans with high fitness values from the final generation and select one among them as the final plan for implementation.

GENERATING FLOOR PLANS

The study area is divided into 400 cells, each of which has an initial allocation of floor type as elaborated in Table 2. At first look, Figure 5a might not seem to be divided into 400 cells. The study area is classified into zones (or cells) based on their usage (Figure 5a and Table 2). Cells belonging to the same category have been combined together and re-arranged to illustrate a floor plan. The study area could very well be like the one shown in Figure 5b that shows an alternative representation for the same floor area and represents a more detailed and conventional display. In the case of a plan like figure 5b, instead of uniform cells of equal area (or rasters), vectors (or polygons) have to be employed. Otherwise, the methodology described herein holds equally good for any type of representation. For the sake of simplicity and to

| Floor Space Type	FL_Code	Gene
Space for Public Utilities	PBL	0
Food Court	FC	1
Parking Spaces	PS	2
Convention Area	CA	3
Recreational Spaces	REC	4
Library	LIB	5
Commercial Space	CS	6
Commercial Space-IT	CSIT	7
Spaces b/w Floor Types	CSS	8
Emergency/Reserved	ERS	9

Table 2. Gene-Floor Types

facilitate a lucid demonstration of our methodology integrating GA with Visualization, we have considered a relatively simple floor space for this study.

The plans in the starting generation were generated by a random process in which integer values were allotted to the 100 chromosomes. Each of this is a potential solution to the problem considered in this study, corresponding to the 400 zones in the study area. The set of constraints entail the values of certain design zones to remain invariable. During the starting random generation stage, the plans that did not satisfy these constraints were discarded. From this starting generation, the whole GA process involves 100 iterations resulting in a generation with 100 final, feasible plans. In this study, the mutation probability was chosen as 0.05. On the whole, the average time consumed
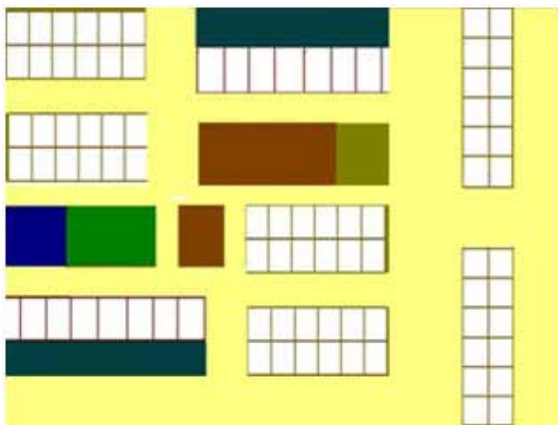
Figure 5a. Study Area – Mall Floor Space
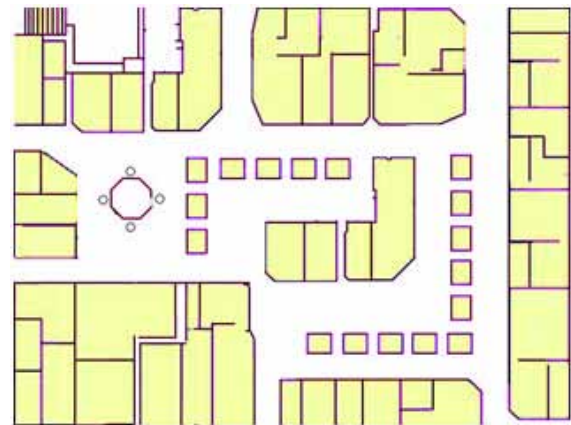
Figure 5b. Alternate Representation - Study Area

for the experiments that were performed on a Pentium-IV machine with 1 GB RAM is 6700 seconds for one execution of 100 generations.

DESKTOP VR RENDERING OF PARETO OPTIMAL DESIGN PLANS

Many GAs generate optimal solutions via iterative optimization procedures. However, the work stops there and then subjective measures are employed to select one plan for implementation. Therefore there is an increasing need for tools or indicators that can efficiently depict design scenes as one comprehensive screenshot rather than a series of non-coherent data layers. Virtual reality visualization can meet such need by facilitating not only presented information, but also enabling seeing and understanding of hidden information among datasets. By using 3D visual scene renderings, planners who are experts in the fields of design planning can identify desirable or undesirable patterns. Aesthetic view quality is of significant importance in design. For instance, a structure blocking the view of a piece of art or some other feature of prominence specifically included to enhance the face value of the shopping mall is undesirable and hence such a design is not judicious. Three-dimensional visualization can greatly

```
#VRML V2.0 utf8

DEF Root_Node Transform { children [
    DEF Food_Court Transform {children [
    #................
    ]}
    DEF Library Transform {children [
    #................
    ]}
    DEF Public_Utilities Transform {children [
    #................
    ]}
    DEF Residential Transform {children [
    #................
    ]}
    DEF Commercial Transform {children [
    #................
    ]}
    DEF Convention_Area Transform {children [
    #................
    ]}
    DEF Recreational Transform {children [
    #................
    ]}

    DEF Emergency_Areas Transform {children [
    #................
    ]}
    DEF Commercial_IT Transform {children [
    #................
    ]}
]}
```

Figure 6. Code Snippet Showing Grouping of Scene Objects

facilitate the study of the aesthetic quality of a plan. Furthermore, such visualization tools can be also integrated into public participation systems and allow non-planning experts to get actively involved in the selection process.

Virtual reality has been described in many ways by various researchers. Generally, however, virtual reality can be defined as the application of an artificial environment generated by computer technology to simulate some targeted activity (Connolly, 2005). Virtual environments cover a wide continuum of involvement, including those that are fully immersive for the user - involving multi-sensory input and interactive movement controlled by the user (immersive VR), partially virtual and real environments (augmented VR), or virtual environments fully contained within a two-dimensional computer screen (desktop VR).

In the example presented in this paper, the authors utilize desktop VR to display the results of the Pareto design plans. Regarding the visualization advantage that virtual technologies can provide, Mohler (2000) stated:

> "Virtual reality (VR) technologies provide a unique method for enhancing user visualization of complex three-dimensional objects and environments. By experience and environmental interaction, users can more readily perceive the dimensional relationships of objects typically portrayed through static multiview or pictorial representations. (p. 151)"

A scene-tree construction is used in Virtual Scene Renderings. The root or the parent object consists of whole scene grouped together and all the other components are grouped under this parent object using 'parent-child' relationships (Figure 6). Individual scene elements corresponding to each floor type such as library, convention area, residential, commercial, recreational, public utilities were created from scratch and were positioned according to their corresponding positions as per the Pareto plan obtained in the previous step. For complex objects including multiple parts, various object parts are grouped to form parent objects, leading to complete objects that are once again

combined and positioned properly to form bigger objects resulting in the final 3D scene.

Two Pareto-plans with the highest fitness values were selected and visualization plans generated for these. Figure 7 illustrates the various scene elements generated for the virtual scene and Figure 8 shows the complete 3D virtual world composed of all these elements. The individual scene elements are positioned based on their corresponding locations according to the Pareto plan.
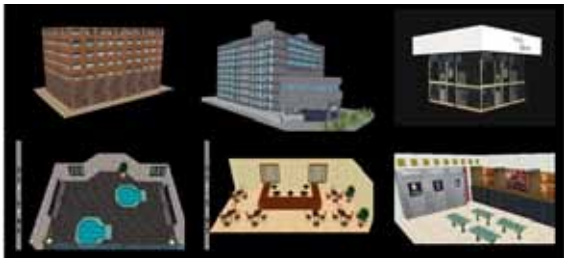
Figure 7. VR scene elements corresponding to various categories: Clockwise from Top-Left-Residential, Convention Area, Library, Recreational, Food-court, Public-Amenities

Figure 8. Populating the VR scene with elements corresponding to Pareto Plan

Figure 6 above shows a detailed 3D design corresponding to the Pareto plan. Using such a display, designers and planners can see the potential solution instead of discussing in an abstract manner. Thus, the usefulness of visualization in evaluating CPOPs (Competing Pareto-optimal plans) is evident. The plans can be compared in a very systematic manner by evaluating them based on the objectives considered in this study. Moreover, using various LODs (Level of Detail) and studying the same scene from multiple viewpoints, numerous issues that might not otherwise be obvious can be identified. Subjective features such as scene quality can be studied in a more reliable manner.

The same scene can be viewed with varying levels of detail. For instance, when viewing from a distance, the finer details are not obvious. This notion can be used to efficiently model the scene. Based on the viewer's position in a scene, the objects can be rendered accordingly.

DISCUSSION

In this study, interactive and navigable virtual worlds were generated, which can efficiently depict design scenario(s) than a set of paper-based or PC-based 2D data representations. Nevertheless, unless the data is transformed into the 3D format it is not of significant use to planners and decision makers, since interpreting voluminous statistical data is a mammoth and cumbersome task. Visualization aids in understanding the overall scene composition and understanding its function holistically. A closer look at figure 6 shows that some of the originally included floor plans cannot be found. This is because the constraints did not ensure that all the FL_Types were strictly to be represented minimally in the final plan. Hence, after including this in the GA, the plans were regenerated (Figure 9).

Figure 9. Pareto plan including elements such as library and reserved space (Orange)

One prominent advantage of using visualization models is that even a bird's eye view can provide enormous details to the observer. For instance, planners can identify desirable or undesirable patterns using visual scene renderings. The ability to view a scene from innumerable perspectives is an essential functionality to capture the links between the various dimensions of a virtual scene. Scene characteristics that are otherwise incomprehensible become evident when using such advanced 3D

visualizations. Furthermore, the software(s) used in this study are Opensource and are web-friendly in the sense that (if the situation demands) hosting them online is extremely straightforward. These worlds can easily be embedded into a HTML/xHTML file or can be displayed on the popular internet browsers with a plug-in for displaying the 3D worlds.

From the above discussion, it follows that the obvious advantage of using virtual worlds for visualizing the competing Pareto-optimal plans (CPOP) is that patterns (desirable or undesirable) can be easily found (Chandramouli et al., 2009). Using varying LODs and by studying the same scene from multiple viewpoints, numerous aspects that might not be obvious otherwise can be found. Subjective features such as scene quality can be studied in a more reliable manner. From the following figure (Figure 10), the use of visualization to study the same scenario from various viewpoints is evident. Using Anchor nodes (in VRML) annotations or additional information can be added to the virtual worlds – these might include a gamut of information including CAD files, other drawings, MS Project files, etc. Additionally, the External Authoring Interface (EAI) of the virtual scene created above provides a valuable means of extending the scene capabilities beyond what can be used using Anchor nodes available within VRML. The EAI provides an excellent means of enhancing the existing functionalities via Java or JavaScript source code. Such code snippets can be plugged-in to provide advanced functionalities include computational capabilities (where necessary).

Figure 10. Scene Viewed from Varying POV (Points of View)

Another crucial aspect that is facilitated by this integration of desktop VR with GA is the evalua-

tion of the aesthetic view quality. Interior as well exterior design is a prominent issue in engineering planning and design today. The ability to foresee the final renderings in 3D before implementation and being able to provide the stakeholders with a concrete product layout even before the construction can begin is a very valuable asset. Such visual representations serve to rise above the challenges imposed by conventional factors such as scale and viewpoints. The functionalities within the VRML browser plug-ins that enable exploring and studying the same virtual world studied from various orientations is of immense value in scene-analysis (Chandramouli et al., 2009). Furthermore, modern browsers provide excellent features whereby scene elements can be translated, rotated, and manipulated in several other ways.

QUALITATIVE SCENE ANALYSIS BASED ON HUMAN EVALUATION AND SCENE MODIFICATION

A GA greatly facilitates the process of exploring the search space effectively and narrows down the search to a limited area with a very high probability of potential solutions as is described in earlier sections. A GA can be used for imposing constraints and formulating objective functions. However, it may not be possible to include all the elements that "need" to be included in the planning process within a GA. That will necessitate the inclusion in the GA innumerable objective functions and as well as many constraints. Despite numerous objective functions and constraints, it is still possible that some important element were not considered. This might subsequently become evident when using the 3D Scene Visualization. Very simply, some aspects might not be evident unless a structure is in place. Once the structure is in place, some mistake might seem obvious to the observer and might find it implausible that the planners could not have considered that at an earlier stage. Hence, after the design process has passed the GA stage, the planners can still study the visualization and incorporate changes accordingly. This enables incorporating the expertise of the decision makers which may not have been pos-

sible in the actual GA process. Some subjective elements pertaining to aesthetic considerations will fall under this category.

CONCLUSION

Today's design problems tend to be multifaceted and the involvement of multiple stakeholders increase the complexity of the number of elements to be considered before finalizing a plan. Even though the search space can be efficiently skimmed using a multiobjective optimization tool such as a genetic algorithms (GA), they still do not provide the decision-makers with a unique solution that can be implemented. The selection of a single solution from the pool of candidate solutions produced at the end of the multiobjective optimization process is by no means trivial. Without exaggeration, it can even be safely stated this might be as critical (if not more) as the actual multiobjective optimization process itself. A solution that has been selected without considering the various perspectives included in the study can seriously undermine the effectiveness of the final solution irrespective of the efficacy of the GA. With these points in consideration, in this study, design planning is formulated as a multi-objective optimization problem, which is solved using genetic algorithms. The study does not stop with merely presenting the results in the form of a Pareto set with a pool of candidate solutions, but visualizes potential solutions using a visualization tool. Visualizing the plans in this manner throws open a plethora of perspectives and simulates the end product that can be visualized, explored, and navigated. This tremendously facilitates the practice of informed decision-making, and in so doing aids the choice of the optimum plan. As mentioned in Section 5 earlier, the online hostability of these scene visualizations greatly enhances the utility of the framework. This not only facilitates the process of obtaining review and feedback from the top-level administrators, but also paves the way for obtaining input from diverse audience owing to the ubiquity of the internet.

REFERENCES

Balling, R., Taber, J., Brown, M., & Day, K. (1999). Multiobjective urban planning using a genetic algorithm. ASCE Journal of Urban Planning and Development, 125(2): 86-99.

Balling, R., Powell, B. & Saito, M. (2004). Generating future land-use and transportation plans for high-growth cities using a genetic algorithm. Computer-Aided Civil and Infrastructure Engineering, 19(3), 213–222.

Chandramouli, M., Huang, B., & Xue, L. (2009). Spatial change optimization: Integrating GA with visualization for 3D scenario generation. Photogrammetric Engineering & Remote Sensing, 75(8): 1015-1023.

Connolly, P. E. (2005). Virtual reality & immersive technology in education. International Journal of Information and Communication Technology Education, 1(1), 12-18.

Goldberg, D. E. (1989). Genetic algorithms in search, optimization, and machine learning. Reading, Massachusetts: Addison-Wesley.

Mohler, J. L. (2000). Desktop virtual reality for the enhancement of visualization skills. Journal of Educational Multimedia and Hypermedia, 9(2), 151-165.

Seixas, J., Nunes, J.P., Louren, P., Lobo, F., and Condado, P. (2005). GeneticLand: Modeling land use change using evolutionary algorithms. Proceedings of 45th Congress of European Regional Science Association, Land Use and Water Management in a Sustainable Network Society, Vrije Universiteit Amsterdam, 23-27.

Stewart T. J., Janssen R., & van Herwijnen, M. (2004). A genetic algorithm approach to multiobjective design planning. Computers & Operations Research, 31, 2293–2313.

Spence, R. (2007). Information visualization: Design for interaction (2nd ed.). Harlow, England: Pearson Prentice Hall.

Tufte, E. R. (1990). Envisioning information. Cheshire, Connecticut: Graphics Press.