Optimizing Highway Networks: A Genetic Algorithms and Swarm Intelligence Based Approach

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Abstract

Optimizing highway alignments between given end points is a complex problem since there are numerous alternatives to connect two points in space. The initial efforts to design a highway were primarily manual and based on human judgment. Later, a number of search algorithms were developed to find an optimum alignment after formulating a number of alignment significant costs such as earthwork and pavement costs. Genetic Algorithms (GAs) were recently used to optimize highway alignments and were proven to be very effective due to their ability to avoid getting trapped in local optima while searching for a global optimum solution. A Geographic Information System (GIS) was integrated with GAs for practical application, which allowed working directly with real maps. The genetic approach however, had two main weaknesses: (1) a predetermined number of generations through which the search for an optimal solution was to be carried out, was necessary. It was a usual practice to continue searching through sufficiently large number of generations to ensure that global optimal solution was reached, which increased the computational burden considerably, (2) the integration with GIS while allowed working directly with real maps, further increased the computational burden due to the additional computation necessary in the GIS environment. In order to address the computational burden issue, here we introduce an alternative approach using Swarm Intelligence (SI) for highway alignment optimization. We perform a test example which indicates that swarm intelligence reduces the computational burden significantly.

Keywords: Highway Alignment Optimization, Geographic Information Systems, Genetic Algorithms, Swarm Intelligence.

Introduction

Optimizing highway alignments between given end points (Figure 1) is not a new problem. Successive efforts have been made to solve this problem. Most earlier methods (Garrison and Marble 1958; Boukidis and Werner 1963; Howard, et al. 1968; OECD 1973; Nicholson 1976; Trietsch 1987; Chew, et al. 1989) used traditional search techniques such as dynamic programming, gradient-based methods, and enumeration. Also, earlier methods used only a subset of costs that would influence the selection of alignments. This simplification while making the optimization feasible through one of the traditional techniques reduced the reliability of the solution.

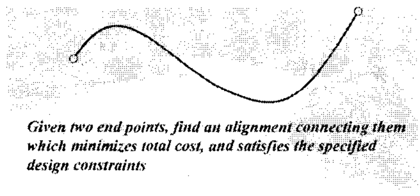


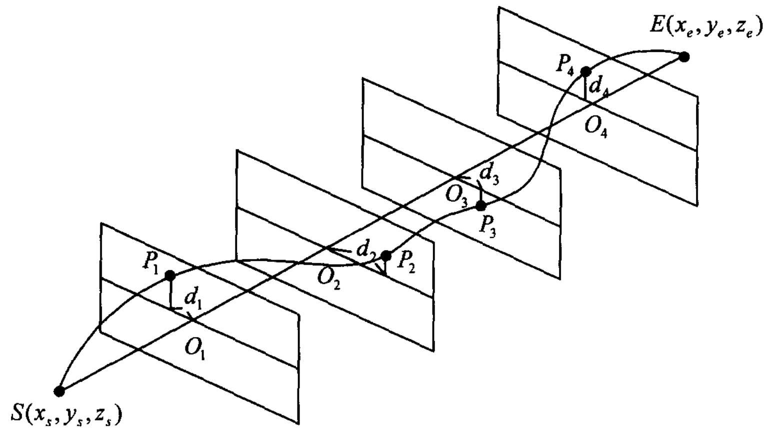
Figure 1. The highway alignment optimization problem.

Traditional search algorithms thus, fail to solve realistic problems due to the oversimplifying assumptions necessary to employ the algorithms; therefore, other alternatives approaches or customized heuristics need to be developed. Jong (1998; see also Jong and Schonfeld, 2002) introduced Genetic Algorithms (GAs) for highway alignment optimization in which eight customized genetic operators were used to obtain an efficient and near global solution. Jha (2000; see also, Jha and Schonfeld, 2000a; Jha, 2002) extended Jong's work by integrating GAs to Geographic Information Systems (GISs) to work directly with real maps to solve real-world problems.

In this paper we focus on the computational issues associated with the GIS-GA integration in highway alignment optimization. In GAs a predetermined number of generations through which the search for an optimal solution is to be carried out, is necessary. Consequently, it is a usual practice to continue searching through sufficiently large number of generations to ensure that global optimal solution is reached, which increases the computational burden considerably. Furthermore, the GIS-GA integration makes the search operation significantly slow primarily due to the large number of computations necessary in the GIS environment. In order to ease the computational burden we develop an alternative approach using Swarm Intelligence (SI). Both GAs and SI are applied to an example study to examine their relative merits.

The GA Formulation

GAs were first customized for highway alignment optimization between given end points by Jong (1998). It was based on the principles of orthogonal cutting planes. According to that method the straight line connecting the end points was vertically cut at equally spaced intervals and orthogonal planes were drawn at those intervals (Figure 2). It was then shown that the optimum alignment will always cross through exactly one point lying along each plane. The number of intervals was user specified. While one would want to choose sufficiently large number of intervals for improved precision it was found that computational burden was significantly high when large number of intervals were chosen. Therefore, number of intervals to be selected depended on precision requirements.



Notation Key: S, E = start and end points for alignment construction
O_i's = equally spaced points along the straight line connecting the start and end points
P_i's = points along the vertical *x-y* planes through which the alignment crosses, also known as Points of Intersection (PIs)
d_i's ,= the axes that passes through O_i's and parallels the *x-y* plane, with O_i's as their origin

Figure 2. The orthogonal cutting planes drawn at equally spaced intervals.

Genetic Encoding and Initial Population

From Figure 2 it can be seen that each intersection point is determined by two variables, the abscissa and ordinate on the associated vertical cutting plane. For an alignment with n intersection points, the encoded solution will consist of $2n$ genes. Therefore, the chromosome is defined as:

$$\Lambda = [\lambda_1, \lambda_2, \lambda_3, \lambda_4, \ldots\ldots, \lambda_{2n-1}, \lambda_{2n}] = [d_1, z_1, d_2, z_2, \ldots\ldots, d_n, z_n] \tag{1}$$

where: Λ = chromosome

λ_i = the i^{th} gene, for all $i = 1, \ldots\ldots, 2n$

(d_i, z_{i_i}) = the coordinates of intersection point on the i^{th} vertical cutting plane, for all $i = 1, \ldots\ldots, n$

It can be easily seen that the mappings between the genes in a chromosome and the coordinates of the intersection points are:

$$\lambda_{2i-1} = d_i, \qquad \forall i = 1, \ldots\ldots, n \tag{2}$$

$$\lambda_{2i} = z_i, \qquad \forall i = 1, \ldots\ldots, n \tag{3}$$

The alleles of odd genes in a chromosome will be limited to the range of the corresponding abscissa. That is

$$d_{iL} \le \lambda_{2i-1} \le d_{iU}, \qquad \forall\, i = 1, \ldots.., n \tag{4}$$

Genetic Operators

Eight different types of genetic operators are employed to solve the optimization problem. The first four are mutation-based operators, while the last four are crossover-based. To fit the nature of the problem, all operators are intentionally designed to work on the decoded intersection points rather than a single encoded gene.

The Optimal Search

The optimal search is performed by first generating an initial population and applying the genetic algorithms to search for a better solution over successive generations. The sum of alignment costs expressed as a function of (d_i, z_{l_i}) is treated as the objective function which is to be minimized. Highway costs used here are extensively discussed in Jong (1998) and Jha (2000). It is noted that a real alignment is generated by connecting S, P_i's, and E, and fitting appropriate curves. The resulting alignment is smooth and continues and satisfies AASHTO (2001) design requirements. Furthers details on curve fitting approach are available in Jong (1998).

Swarm Intelligence

Swarm-intelligence (Bonabeau et al., 1999; Dorigo et al., 1996 and 1999) is the field covering algorithms based on and inspired by the collective behavior of social insect colonies and other animal societies. Ant System is a new metaheuristic for hard combinatorial optimization problems. Dorigo et al. (1996 and 1999) applied ant algorithm to traditional optimization problems such as routing problems and the Traveling Salesman Problem (TSP), and showed that it yielded superior results and was computationally efficient compared to other methods.

The Swarm Intelligence Customized for Highway Alignment Optimization

An ant algorithm based formulation for 2-dimensional (2-D) highway alignment (i.e., horizontal alignment only) optimization was developed by Jha (2001). That formulation is modified here for a 3-D highway alignment (both horizontal and vertical alignment) optimization. Let $i = 1, \ldots, n$ be the number of orthogonal cutting planes (0 and n+1 represent start and end points, respectively). The main difference between applying the ant approach to the current problem and other problems (such as the TSP) that have been tried is that in the present case intermediate destinations (P_i's in Figure 2) in ant's travel path are not known where as in a TSP cities are known and fixed. Therefore, in our approach P_i's (Figure 2) which are treated as the intermediate destinations in ant's travel path, are randomly generated. It is noted that even in the genetic approach P_i's are randomly generated; thereafter, curves are fitted to construct a real alignment. In ant algorithm ant visibility and amount of pheromone laid on links that are visited by the ants drive the search for an optimal solution, similar to genetic operators in the genetic approach.

It is assumed that each artificial ant starts at the beginning point for alignment construction and ends its tour at the end point for the alignment construction. Let $b_i(t), \quad i = 1,\ldots,n$ be the number of ants at the PI i at time t and let $m = \sum_{i=1}^{n} b_i(t)$ be the total number of ants. It is further assumed that each ant is a simple agent with the following characteristics: (1) it always chooses a randomly generated point (PI) along successive orthogonal cutting planes to go to with a probability that is a function of the amount of trail present on the connecting edge; (2) the ants are forced to make legal tours and transition to already visited points are disallowed until a tour is completed; and (3) the ants lay *trail* on each segment connecting (i, j) visited after completing a tour. Let $\tau_{ij}(t)$ be the intensity of trail on edge (i, j) at time t. Each ant at time t chooses the next point, where it will arrive at time (t+1). The m moves carried out by the m ants in the interval (t, t+1) is called an *iteration* and once each ant has visited all n points then one *cycle* is completed. After every cycle the trial intensity is updated according to the following formula:

$$\tau_{ij}(t+n) = \rho\tau_{ij}(t) + \Delta\tau_{ij} \tag{7}$$

where ρ is a coefficient (<1) such that $(1-\rho)$ represents the evaporation of trial between time t and t+n, and $\Delta\tau_{ij}$ is specified as:

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \tag{8}$$

In Eq. (8) $\Delta\tau_{ij}^{k}$ is the quantity per unit length of pheromone laid on edge (i, j) by the k-th ant between time t and t+n, which is specified as:

$$\Delta\tau_{ij}^{k} = \begin{cases} \dfrac{Q}{C_k} & \text{if the k - th ant uses edge(i, j) in its tour} \\ & \text{(between time t and t + n)} \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

where Q is a constant and C_k is the alignment cost for the alignment that is constructed by connecting the start, end, and intermediate points (PIs) visited by the k-th ant and fitting appropriate curves. The intensity of trial at time 0, $\tau_{ij}(0)$, is set to a small positive constant c. The transition probability from point i to j for the k-th ant, $p_{ij}^{k}(t)$ is defined as:

$$P_{ij}^k(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^\alpha [\eta_{ij}]^\beta}{\sum_{h\in\Omega_k} [\tau_{ih}]^\alpha [\eta_{ih}]^\beta} & \text{if } j \in \Omega_k \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

where Ω_k is the set of feasible points along the orthogonal cutting planes to be visited by ant *k*, which is updated for every ant after every move, and η_{ij} is the visibility expressed as:

$$\eta_{ij} = \frac{1}{(d_{ij} + z_{ij} + l_{ij})} \tag{11}$$

In Eq. (11) d_{ij} is the Euclidean distance between points *i* and *j*, z_{ij} is the absolute difference in elevation between points *i* and *j*, and l_{ij} is the absolute difference in unit land cost between points *i* and *j*. For TSP η_{ij} is expressed as the inverse of distance between *i* and *j* since the objective is to minimize the tour length. In highway alignment optimization the objective is to minimize total highway cost. The cost components used are the ones that would influence the alignment selection such as right-of-way, earthwork, pavement, travel-time, vehicle operating, and accident costs. The reasons distance, elevation difference, and unit land-cost difference between successive points are used in defining the visibility in Eq. (11) is that the cost components sensitive to alignment selection depend on these three factors. For example, right-of-way cost depends on unit land cost, pavement and travel time cost depend on distance, earthwork and vehicle operating cost depends on elevation difference, and accident cost depends on both distance and elevation difference.

An Example Study

We first apply the GAs to optimize a horizontal alignment in an example using real maps. A new 7.32 m (24 ft) wide 2-lane road with 0.915 m (6 ft) shoulders is to be built in Talbot County, Maryland (Figure 3). The proposed road is to be built as a bypass between the start and end points (Figure 3). The *(x, y)* coordinates of the search space range from 1035893 to 1037690 and from 312906 to 314055, respectively. The coordinates of start and end points are (1036782, 313042) and (1036900, 314022), respectively. The Euclidean distance between the start and end points is 301 m (987 ft). The geographical shapes with darker shades represent higher cost regions. The largest darkest region represents portion of the Chesapeake Bay, which is assigned a unit cost value of $1000/sq. ft. A stop criterion of 100 generations is applied for optimal search. Connection with existing roads requiring intersection and interchange design as well as bridge construction over water is not considered in the present case. The intersection, interchange, and bridge designs may either be considered as a post process or can be considered along with other costs within GAs. Additional work is necessary to comprehensively formulate these costs. Kim (2001) has provided a preliminary formulation for intersection, interchange, and bridge consideration, which needs to be incorporated in the present example; however, it is skipped here since that is not the focus in this work.

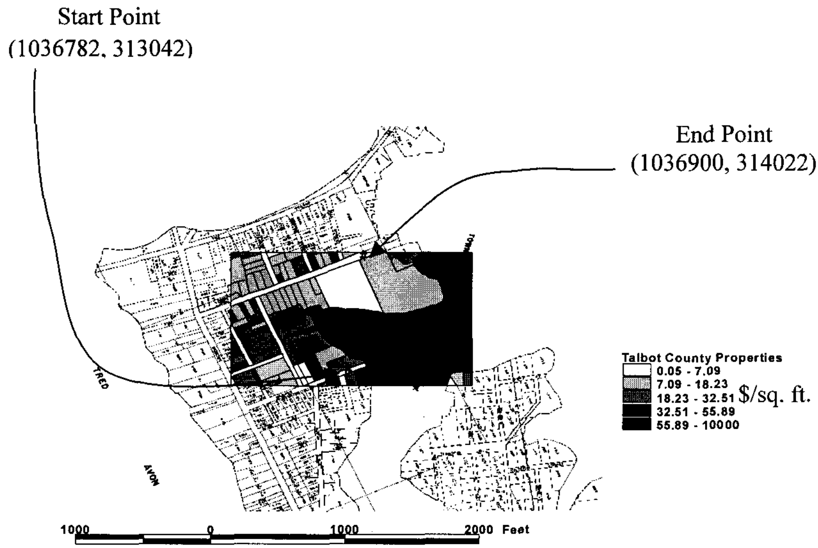


Figure 3. Geographic Map of the Example Study

Compactness Analysis

Jha (2000; also Jha and Schonfeld, 2000b) performed a compactness analysis to compute right-of-way cost that was more realistic and reliable. Most earlier methods only assumed that the right-of-way cost was simply the fractional area of a land parcel taken by the proposed alignment multiplied by the unit cost of the land parcel. In his approach Jha (2000) analyzed the usability of the remainder pieces of lands and also considered damage to the existing houses and structures. He however, observed that the compactness analysis significantly increased the computational burden.

For the present test example we compute right-of-way costs with and without compactness analysis. It is observed that compactness analysis results in higher right-of-way cost indicating that values of unusable properties and structures are considered in the cost computation. The GAs with usability analysis attempt to minimize the number of unused pieces while without usability they only consider fractions of lands taken by the alignment. Usability considerations increase the precision in computing right-of-way cost, but the resulting cost need not be lower. The difference in right-of-way cost (expressed as percentage) is plotted over successive generations in Figure 4. At the 28^{th} generation the difference is about 11%, which is quite significant. It is notable that the difference in right-of-way cost with and without compactness will vary from one case to another. In dense urban areas with small land parcels and expensive houses the compactness analysis will result in significantly higher right-of-way costs.

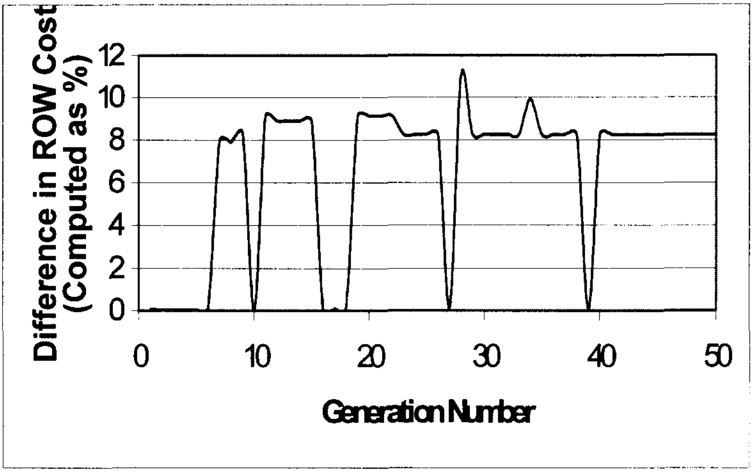


Figure 4. Effects of compactness analysis on Right-of-Way (ROW) cost

Figure 5 shows the computing times (a Pentium III 550 MHz PC with 128 MB RAM is used) over successive iterations with and without usability, respectively. It can be seen that computing time per iteration is smaller without usability since fewer land pieces are needed to be analyzed. The average computing times per iteration with and without usability analysis is about 12 sec. and 3 sec., respectively.

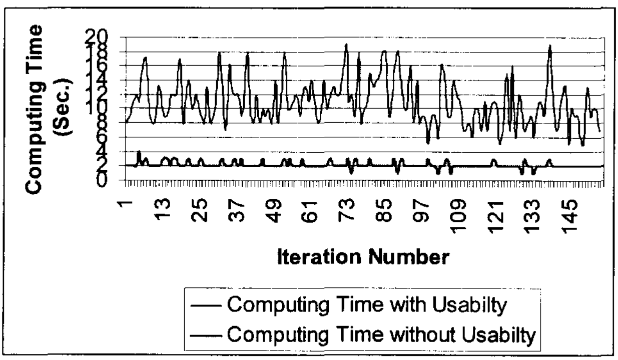


Figure 5. Computing times with and without usability

Analysis of GA Results

The total cost of alignment (the large part of the cost is user cost, i.e., vehicle operating, travel time, and user costs) at generation 1 is $44.9 million. The solutions for the entire population over 100 generations are plotted in Figure 6. The minimum objective function value at successible generations is also plotted, as shown in Figure 7. Figures 8 and 9 show the mean and standard deviation of the solutions over successive generations.

Figure 7 implies that the changes in objective function value becomes very small after about 64 generations. Figure 8 shows that the average value of the objective function generally decreases over successive generations. Figure 9 indicates that while there is some variation among population members at later generations, the variation tends to decrease over successive generations.

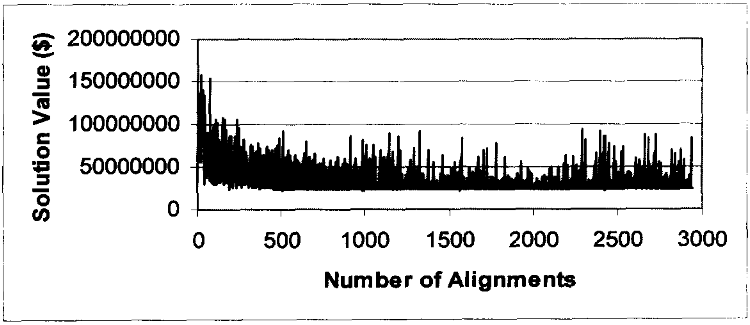


Figure 6. Plot of candidate alignments for the entire population

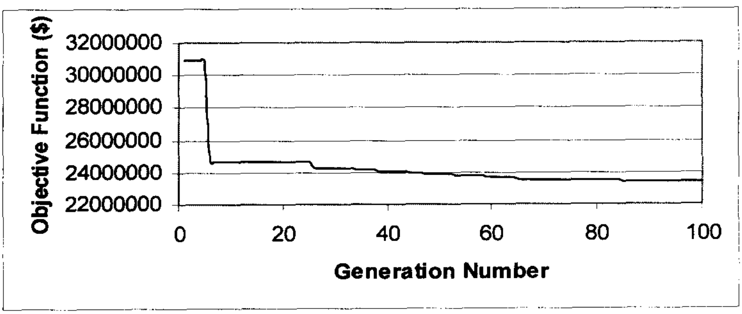


Figure 7. Objective function over successive generations

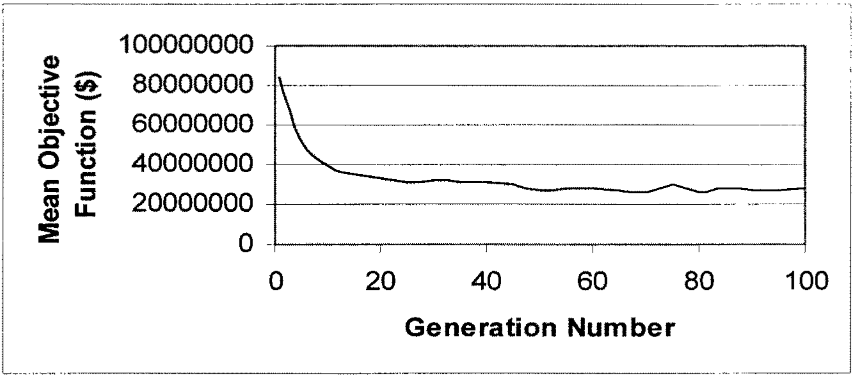


Figure 8. Mean objective function over successive generations

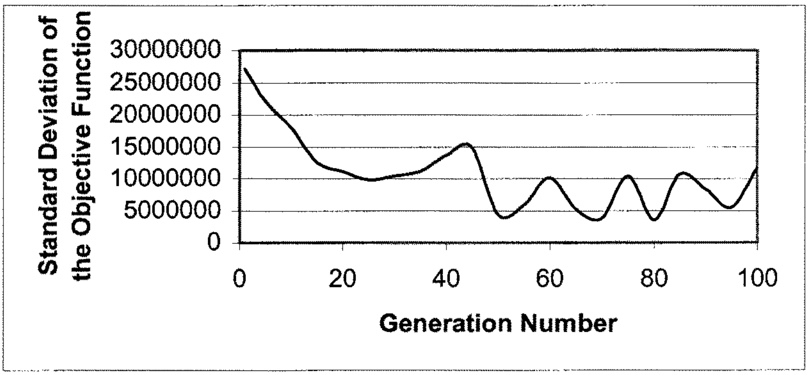


Figure 9. Standard deviation of objective function over successive generations

The optimized alignment obtained at the 100^{th} generation (Figure 10) has circular curves that satsify the AASHTO (2001) minimum radius requirements for safe movement of traffic at the specified design speed. It also avoids high cost areas. The total optimized alignment length is 381 m (1,249 ft), its total cost is $23.43 million, and its location-depedent cost is $ 0.90 million. The total cost function used in optimization consists of five costs, i.e., length-dependent costs (e.g., construction and maintenance costs) and location-dependent costs (e.g., right-of-way cost), which are classified as supplier cost and vehicle operating, travel-time, and accident costs, which are classified as user costs. In the optimized case these costs are $1.54, 0.90, 0.99, 17.31, and 2.69 (in millions), respectively. Thus, the total supplier cost over the design life of that road section is $2.44 million. In a more complex geographic space, with greater land use variability, the optimized alignment would be more winding.

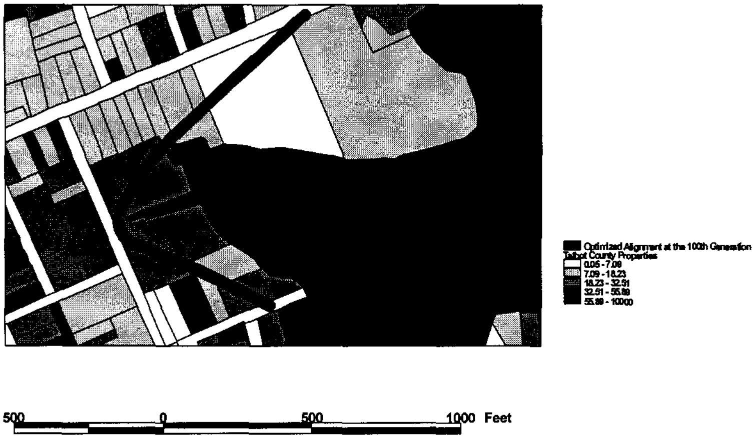


Figure 10. Optimized alignment

Effects of Map Density on Computational Burden

The computations necessary for area and perimeter calculations when working with real geographic maps in the GIS environment significantly increase the computing time. As noted earlier, the average computing time for each candidate alignment evaluation with and without usability analysis is 12 and 3 sec. (Figure 5), respectively. In GAs several candidate alignments need to be evaluated in every generations. The actual number of evaluations (we call it "iterations" within a generation) required in a generation depends of the number of genetic operators. For example, if 4 of the 8 genetic operators are applied then for 100 generations of search 3,200 randomly generated candidate alignments will need to be evaluated. Please refer to Jong (1998) for further details on this issue.

The computing time will depend on map density (number of properties or parcels per unit area of the search space). To examine the variation of computation burden with map density 4 test scenarios are created: (1) a one square mile grid having 100 parcels, i.e., map density (parcels/sq. mi.) = 100, (2) a one square mile grid having 900 parcels, i.e., map density (parcels/sq. ft.) =900, (3) a one square mile grid having 10,000 parcels, i.e., map density (parcels/sq. mi.) =10,000, and (4) a one square mile grid having 1 million parcels, i.e., map density (parcels/sq. mi.) $\approx 10^6$. Figure 11 shows the computing time versus map density. It shows that while the computing time generally increases with the map density, the rate of increase is not linear. Note that these scenarios are run without the usability analysis meaning that the computing times with usabilty analysis will be much higher. Moreover, these times are on a Pentium III 550 MHz PC with 128 MB RAM. The program will run more efficiently on faster computers.

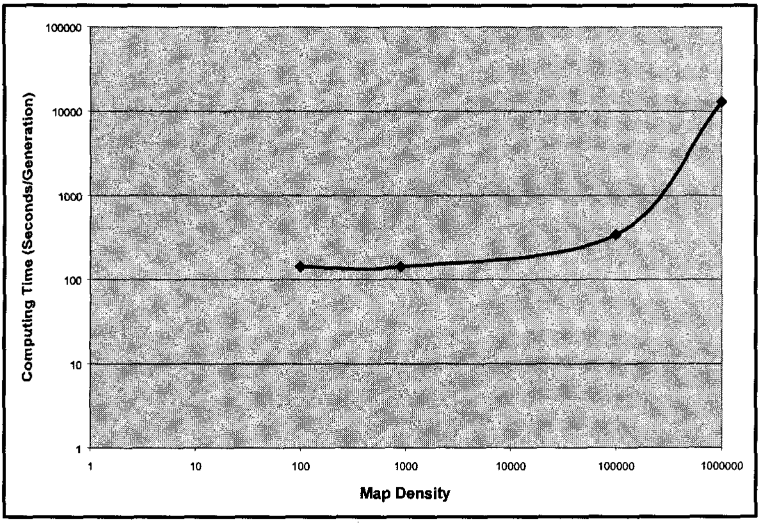


Figure 11. Computing time vs. map density

Optimization with Swarm Intelligence

The same example as described above, was optimized with swarm intelligence (SI). The number of ants used was assumed to be 1,000. The number of intermediate cutting planes was assumed to be 10,similar to that assumed in the genetic approach. The convergence criterion was set to having at least 95% of the ants pass through the same PI's. The optimized solution was identical to that obtained with GAs, but, it was obtained much quicker. The optimized solution was obtained in about 100 iterations compared to over 3,000 iterations required with GAs. With usability analysis assuming that the average computing time per iteration on a Pentium III 550 MHz PC with 128 RAM was 12 sec./iter., the SI approach resulted in a saving of about 10 hours. For much larger problems when thousands of land parcels need to be analyzed, the time savings in computation may be astronomical.

Conclusions and Future Work

GAs and SI are applied to optimize highway alignments using real maps when integrated with a GIS. The relative merits of the two approaches are compared to examine the precision of the solutions and the computation burden. The results indicate that the SI approach is superior in terms of computation efficiency. Additional work is necessary to apply SI to examples with greater land variability, with the option of intersection, interchange, bridge, and tunnel designs, and for highway network optimization.

Acknowledgements

The author wishes to thank Dr. Paul Schonfeld of University of Maryland, College Park, Dr. Dusan Teodorovic of Virginia Tech., and Dr. Eungcheol Kim of Hanyang University, South Korea for their support in completing the research. The work is an extension of the highway design optimization research work carried out at the University of Maryland, College Park between 1996-2000, which was funded, in part, by the Maryland State Highway Administration. It is anticipated that a doctoral student at the Morgan State University will work on further extensions to the highway alignment optimization problem such as network optimization.

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