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ORIGINAL ARTICLE

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Heuristic planning techniques applied to forest road profiles

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Abstract Two heuristic techniques, the genetic algorithm (GA) and Tabu search (TS), both with an embedded linear programming routine for earthwork allocation, were compared to a manually designed forest road profile. The manually designed road length was 345.7 m and its average gradient was 14.1%. The best costs of the profiles designed by GA and TS, without changing the placement of control points, were less than that designed manually. The best cost found by GA was almost the same as the global optimum solution. While TS could not find a better solution than GA, it usually found a good solution in less time. It was not possible to search all alternatives by changing the placement of control points and find the global optimum solution within a reasonable time. However, it can be concluded from the results that both GA and TS found good solutions within a reasonable time. Since it is not possible to manually evaluate many alternatives, road designers should find heuristic techniques helpful for design of the road profile. Moreover, the effect of the number of control points on construction costs was examined. The results indicated that increasing the number of control points reduces the construction costs. However, driving safety and comfort might be decreased.

Key words Forest road design · Genetic algorithm · Tabu search · Linear programming

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Introduction

Forest roads have an important role in managing forest resources. They need to be constructed such a way that forestry workers and machines can gain access to operational sites and carry out operations safely and efficiently. On the other hand, forest roads are at risk of road surface erosion and are subject to cut-and-fill slope failures. Therefore, it is important to design forest roads by considering not only cost efficiency but also the appropriate management of water and soil.

Akay (2003) developed a 3-D forest road alignment optimization model, TRACER, to help the forest road designer with a quick evaluation of alternatives in order to design a path with the lowest total cost taking into account construction, future maintenance, and transportation costs while conforming to design specifications and environmental requirements. The model relies on a high-resolution digital elevation model (DEM), for example one obtained from LIDAR (light detection and ranging), to provide terrain data for supporting the analysis of road design features (Reutebuch et al. 2000). After a designer has decided on control points on a 3-D graphic interface, the model automatically generates horizontal and vertical curves, cross-sections, and calculates construction, maintenance, and transportation costs. This ensures road feasibility considering terrain conditions, geometric specifications, and driver safety. It employs optimization techniques using linear programming to minimize earthwork allocation costs and a heuristic technique (simulated annealing, see Dowsland 1993) to optimize vertical alignment. Finally, it estimates the average annual volume of sediment delivered to a stream from the road section with SEDMODL (Boise Cascade, ID, USA, 1999). However, this model relies on a fixed horizontal alignment determined by the designer, who locates a series of control points between two end-points, considering design specifications and environmental requirements.

Ichihara et al. (1996) discussed the methods for designing the optimum vertical alignment considering the placement of control points. They used genetic algorithms to optimize the placement of control points while using dynamic programming to decide the longitudinal grade for the lowest earthwork cost. Dynamic programming has been widely used in the literature and practice to optimize the vertical alignment (Antoniotti 1969; Nicholson 1976; O'Brien and Bennett 1969; Trietsch 1987). In Japan, Kanzaki introduced dynamic programming to decide the longitudinal grade (Kanzaki 1973). The Japan Forest Development Corporation has used this method to plan forest roads. The basic feature of dynamic programming is that the optimum decision is reached stepwise, proceeding from one stage to the next. However, this method is not suitable for problems having complex relationships between the stages which include earthwork allocation or water and soil flow on forest roads.

In this study, we first developed the model to optimize a forest road profile while changing heights at control points without changing the placement of control points. We used two heuristic techniques, genetic algorithm (GA) and Tabu search (TS), in the model to design a forest road profile with minimum construction and maintenance costs, both with an embedded linear programming routine to allocate earthwork. We discussed the accuracy and computation time of these methods compared with the global optimum. We then extended the model to optimize a forest road profile while changing heights at control points as well as the placement of control points. Finally, we discussed the effect of the placement of control points and the number of control points. This study was conducted as part of the development of an automated forest road design program to minimize construction cost, maintenance cost, and to evaluate soil sediment from soil erosion on forest roads. Future work would extend this methodology to optimize horizontal alignment as well as vertical alignment simultaneously, and would evaluate soil sediment from forest roads.

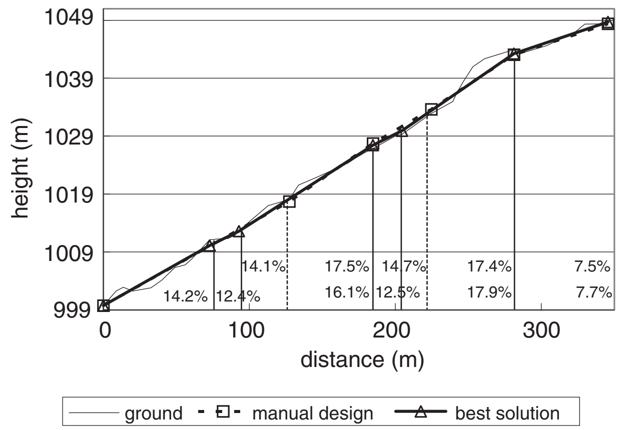

Fig. 1. The example terrain profile (*upper numbers* indicate grades of manual design while *lower numbers* indicate grades of best solution)

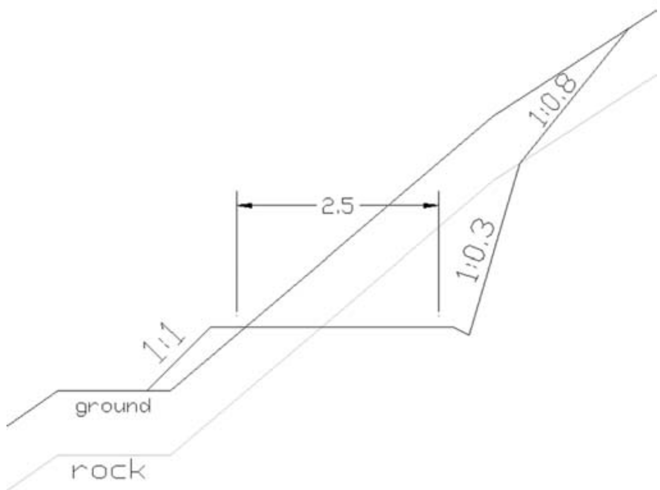

Fig. 2. An example cross-section showing cut-and-fill slope angles, typical running surface width, and depth to rock (not to scale)

Materials and methods

Study site

The example terrain profile is shown in Fig. 1. The length of manually designed road profile is 345.7 m with an average gradient of 14.1%. It has four control points and 17 sections which were located 20 m apart. Longitudinal slopes are changed at control points.

Vertical alignment

The road gradient is limited to less than 18% in this study to accommodate heavy vehicles on aggregate-surfaced roads. Vertical curves are used to connect roadway sections between two grades if the absolute value of the difference between two grades is more than 5%. The minimum curve length is 20 m. In determining a feasible curve length, crest and sag vertical curves are considered separately based on whether the curve length is greater or less than the safe sight distance (Mannering 1990).

Cross-sections

Cross-sections are located perpendicular to the road profile. Cross-sections can be derived from either survey or LIDAR data. They are used to compute earthwork volume and major cost elements for each road stage. An example cross-section is shown in Fig. 2. The road width is 2.5 m, the cut slope is 1:0.8, and the fill slope is 1:1. This program can analyze different types of materials, for example rocks, as subsurface materials. Excavation in rock is at 1:0.3. If a cut slope or a fill slope exceeds 5 m in height, it is assumed that blocks are used to fix a slope at 1:0.3.

Cost calculation

The total cost of each road section is determined using the method of Akay (2003), considering construction and maintenance activities. The road construction cost is computed for the following activities: construction staking, clearing/grubbing, earthwork allocation, drainage and riprap, surfacing, water supply/watering and seeding/mulching. The maintenance activities consist of rock replacement, grading, culvert/ditch maintenance, and brush clearing. The discounted cost of future road maintenance is estimated to compare the total construction and discounted maintenance cost for alternative profiles. The objective function that minimizes the total cost, T_C, takes the following form:

$$Min\, T_C = C + M_0 \tag{1}$$

where C is the construction cost and M_0 is the discounted maintenance cost. The USDA Forest Service *Region 6 Cost Estimating Guide* (1999) is used to estimate the costs.

Construction staking cost

Construction staking cost is estimated by multiplying the unit costs per kilometer ($778/km) by specified adjustment factors and total road length in kilometers. These factors include ground cover, terrain, section, and travel factors. When the ground cover is denser, the basic unit cost is increased by 15%. The model computes the side slope at each road section to estimate the terrain factor. If the side slope is greater than 30%, the basic unit cost is increased by 25%. When there are more than 60 sections per kilometer, the model increases the basic unit cost by 30%.

Clearing and grubbing costs

The area to be cleared between two consecutive sections is estimated by the model. The clearing and grubbing costs are estimated by multiplying the given unit costs per unit area ($3700/ha) by adjustment factors and total clearing area. The factors include clearing classifications, slash factor, side slope factor, and clearing width factor. Clearing classifications varies based on the density of the ground cover (medium: 1.74). The slash factor depends on the slash treatment method (windrowing: 1.07). The model computes average side slope of two consecutive cross-sections to define the side slope factor. Average clearing width is computed based on the clearing widths.

Earthwork allocation cost

The economic allocation of the earthwork is determined using the linear programming formulation suggested by Mayer and Stark (1981). This formulation considers possible borrow and landfill locations and various soil characteristics along the roadway. It is assumed that the unit cost of hauling is linearly proportional to the hauling distance. The unit costs of earthwork activities do not vary with the amount of material moved, but the soil type at each road stage. In this method, swell factor of the material moved from cut section i, and shrinkage factor of the material compacted into fill section j, are also considered. The objective function Z can be stated as follows:

$$MinZ = \sum_i \sum_j C(i,j)X(i,j) + \sum_i \sum_k C_D(i,k)X_D(i,k) + \sum_p \sum_j C_B(p,j)X_B(p,j) \tag{2}$$

Subject to the following constraints:

1. The amount of cut moved from cut section i to fill section j ($X(i,j)$) plus the amount of cut moved from cut section i to landfill area k ($X_D(i,k)$) are equal to the available amount of cut at cut section i.
2. The adjusted amount of cut moved from cut section i to fill section j ($s_{ij}^f X(i,j)$) plus the adjusted amount of material moved from borrow area p to fill section j ($s_{pj}^f X_B(p,j)$) are equal to the amount of fill required at fill section j. s_{ij}^f and s_{pj}^f are the shrinkage (or swell) factors for material moved from cut section i and borrow area p, respectively.
3. The adjusted amount of cut moved from cut section i to landfill area k ($s_{ik}^f X_D(i,k)$) is equal to or less than the capacity of the landfill k. The shrinkage (or swell) factor for material moved from cut section i and wasted in landfill area k is defined as s_{ik}^f.
4. The amount of material moved from borrow area p to fill section j ($X_B(p,j)$) is equal to or less than the material available in borrow area p.

$C(i,j)$, the unit cost of moving and compacting soil from cut section i to fill section j, is estimated based on the unit cost of excavation (u_e: \$1.61/m^3), hauling (u_h: \$1.3/m^3-km), and compacting (u_c: \$0.58/m^3), assuming that the costs are linearly proportional to the quantities. The formulation for adjusted quantities based on the distance between the centers of the cut section i and the fill section j, d_{ij}, is:

$$C(i,j) = u_e + s_i^h (u_h d_{ij} + u_c) \tag{3}$$

where s_i^h = swell factor at cut section i. The unit cost of borrow, $C_B(p,j)$, and disposal, $C_D(i,k)$, are determined similarly. $C_B(p,j)$ is estimated based on unit cost of excavation (u_e: \$1.81/m^3), hauling (u_h: \$1.3/m^3-km), and compacting (u_c: \$0.58/m^3). $C_D(i,k)$ is estimated based on unit cost of excavation (u_e: \$1.61/m^3), hauling (u_h: \$1.3/m^3-km), and disposal (u_d: \$0.1/m^3). It is assumed that excavated rock at cut section i is disposed of at the landfill area. The unit cost of rock is estimated based on unit cost of excavation (u_e: \$3.0/m^3), hauling (u_h: \$1.3/m^3-km), and disposal (u_d: \$0.1/m^3). The estimated swell factors in haul and shrinkage factor in embankment for the soil along the roadway are 1.4 and 0.75, respectively. For borrow material, these factors are 1.2 and 0.9, respectively. For rock, these factors are 1.6 and 1.3, respectively. It is assumed that the block unit cost is \$161.0/m^2.

It is assumed that a borrow and a landfill area with sufficient capacities are located at the beginning of the road section. It is also assumed that it is physically possible to move earthwork between points *i* and *j*.

Surfacing cost

The surfacing cost is computed based on the type and required quantity of the surfacing material and haul distance. In forest roads, 7.5–15 cm size rock is used for the base course with 25 cm depth. The rock size and depth of the traction surface is assumed to be determined by the road grade. In the model, on grades less than 16%, 4-cm rocks are used in the traction surface with 8 cm depth. If the grade is greater than or equal to 16%, 2.5-cm rocks are used in a traction surface with 10 cm depth (Kramer 2001). The quantity of the surfacing material depends on the length and width of the road section, and surfacing depth. The unit costs (including rock purchasing or production, hauling, processing, and testing) for rock types are estimated as follows: pit run is \$3.92/m^3, good quality base course rock (7.5 cm) is \$7.85/m^3, traction surface rock (4 cm) is \$11.77/m^3, and finer traction surface rock (2.5 cm) is \$15.69/m^3.

Water supply and watering cost

Watering is required to control dust and to retain fine surface rock when surface materials are too dry. Watering cost depends on the estimated unit cost of water (\$3/kiloliter), the amount of water required for excavation (26 liter/m^3), surfacing operations (114 liter/m^3), and haul distance (30 km). It is assumed that the required amount of water is purchased and the truck is equipped with a water pump.

Seeding and mulching cost

The minimum amounts of material used for seeding, fertilizing, and mulching are 30, 150, and 3000 kg/ha, respectively. The total cost is estimated by multiplying the estimated unit costs of seeding (\$0.33/kg), fertilizing (\$0.08/kg), and mulching (\$0.08/kg) by the amount of materials used per unit area, the total project area and the application cost (includes overhead, equipment, transportation, and labor costs, \$550/ha).

Drainage and riprap costs

Drainage cost is computed based on the unit costs (material, installation, elongation, treatment, and special item costs) per lineal meter of the culvert (\$25/m) by the culvert length in meters. In forest roads, 15–20-cm size rocks are commonly used as riprap material to reduce ground disturbance due to surface runoff and falling water on the downspout. The riprap cost is estimated by multiplying the basic unit cost of riprap per cubic meter (\$10/m^3) by the required volume of rock used, in cubic meters.

Maintenance costs

Road maintenance generally includes replacing the aggregate, performing blading, and maintaining culverts and ditches. Rock replacement cost, Cf_r is assumed to vary with the timber volume transported over the road (i.e., 2.5 cm rock displacement for every 4500 m^3 timber haul), road width, and length of the road stage. The blading cost, Cf_b is computed based on the assumptions that for each 9000 m^3 transported, at least one blade maintenance operation is required, the unit cost of blading (\$0.3/m), and the road length. The cost of maintaining culverts, Cf_c is computed depending on the basic unit cost of maintaining a culvert (\$15 per culvert) and the number of culverts installed along the roadway. The cost of maintaining ditches, Cf_d and brush, Cf_{cb} is calculated based on the estimated unit costs, \$0.2/m and \$0.25/m, respectively, and length of the road stage to be maintained.

Finally, the discounted maintenance cost, M_0, is computed using a terminating periodic series approach (Klemperer 1996). The basic formula of this series is:

$$M_{rb0} = \left(Cf_r + Cf_b\right)\left(\frac{1}{(1+r)^1} + \frac{1}{(1+r)^{2t}} + \cdots + \frac{1}{(1+r)^{kt}}\right) \quad (4)$$

where M_{rb0} = the discounted cost for rock replacement and blading, r = annual interest rate (e.g., 1%), t = harvesting periods in years (e.g., 5 years), k = number of harvesting periods (e.g., 6). Reformulating Eq. 4:

$$M_{rb0} = \left(Cf_r + Cf_b\right)\left[\frac{1-(1+r)^{-n}}{(1+r)^t - 1}\right] \quad (5)$$

where $n = kt$, estimated total service time (e.g., 30 years) of the road in years or the time when last harvesting occurs. The discounted cost for the culvert and ditch maintenance, and brush cleaning is calculated in a similar way. Then, the discounted maintenance cost is:

$$M_0 = \left(Cf_r + Cf_b\right)\left[\frac{1-(1+r)^{-n}}{(1+r)^t - 1}\right] + \left(Cf_d + Cf_{cb} + Cf_c\right)\left[\frac{1-(1+r)^{-n}}{(1+r)^{t_m} - 1}\right] \quad (6)$$

where t_m = time intervals (e.g., 5 years) for the culvert and ditch maintenance, and brush cleaning.

Vertical alignment optimization

The model generates new road alignment alternatives by systematically searching for the vertical alignment with the lowest total cost. Heuristic combinatorial optimization techniques (genetic algorithm and Tabu search) are used to guide the search for the best vertical alignment that minimizes the sum of construction and maintenance costs while changing heights at control points as well as the placement of control points. Technically feasible grades are considered in this search. The model calculates cross-sections, earthwork volumes, and minimizes earthwork costs using linear programming for each alternative vertical alignment, subject to geometric specifications.

Both GA and TS have successfully solved combinatorial optimization problems. However, the search processes are significantly different. GA begins with randomly generated initial solutions and uses the mechanics of selection, crossover and mutation, in which random numbers are used. On the other hand, TS is based on gradient search and uses a Tabu list which forbids or penalizes the search for certain previously visited solutions to avoid local optimum entrapment. Random numbers are basically not used in TS. Applicability of GA and TS to forest road profiles is examined in this study.

Genetic algorithms

Genetic algorithms (GA) were developed initially by Holland and his associates in the 1970s. Most early applications were in the realm of artificial intelligence, such as game-playing and pattern recognition (Reeves 1993). Applications to combinatorial optimization have also been developed. In road design, Ichihara et al. (1996) used GA to decide the location of control points while using dynamic programming to decide the longitudinal grade for the lowest earthwork cost. Suzuki et al. (1998) planned forest roads for recreation with a digital map. They connected start points, end points, and two randomly chosen points with the Dijkstra method (Smith 1982) to increase driving safety, and reduce earthwork volume and the viewed frequency. Changing coordinates of the intermediate points, they searched for the most suitable route using a genetic algorithm.

First, we generated an initial population of five feasible solutions considering the four control points from the manual design (Fig. 3). The feasible solutions were generated by changing alternative height at control points and end points at intervals of 1 m within 10 m above and below ground height randomly. The height of the start point is assumed to be the same as the ground height. A "chromosome" (a single solution) consists of six "genes" representing the start point, four control points, and the end point. Each gene is encoded as a vertical distance from ground height. In many applications, the component vector, or chromosome, is simply a string of 0s and 1s. Goldberg (1989) suggests that there are significant advantages if the chromosome can be so structured, although a more recent argument by Antonisse (1989) casts doubt on this. Each chromosome in the initial population is evaluated by computing the objective function value, thus each solution must be feasible with respect to the constraints.

Parent chromosomes are then selected based on "fitness" [the better the fitness value (objective function value), the higher the chance of it being chosen]. They are then "mated" by choosing a crossover point at random, then the crossover occurs, and two "offspring" chromosomes (two new solutions) result.

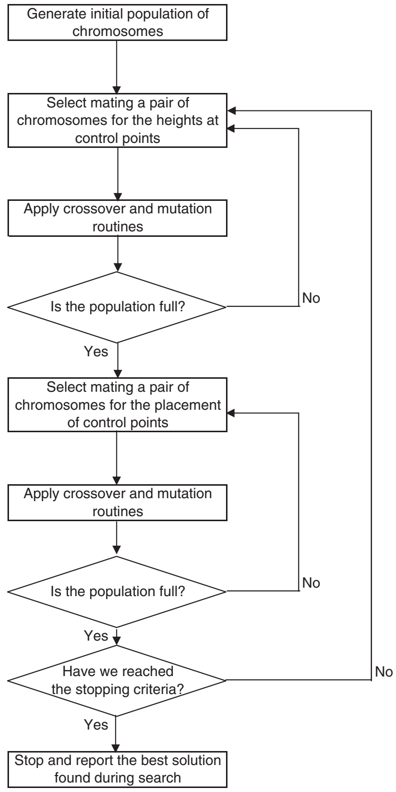

Fig. 3. A flow chart of the genetic algorithm process

$$X = (0,-1,2,7,-9,4)$$
$$Y = (0,-10,5,-4,2,-1)$$

And if the crossover point were noted as being just before the third control point, the pieces prior to the crossover would be

$$X_1(0,-1,2)\ X_2(7,-9,4)$$
$$Y_1(0,-10,5)\ Y_2(-4,2,-1)$$

And the resulting offspring would become:

$$X_1Y_2(0,-1,2,-4,2,-1)$$
$$X_2Y_1(0,-10,5,7,-9,4)$$

A random mutation may then be applied to these offspring. If a random number on the range between 0 and 1 is less than the mutation probability, the current vertical distance of a randomly chosen gene will randomly change. The small number of genes would lead to a larger than normally used mutation rate, 1–5% (Ichihara et al. 1996). De Jong (1975) has been quoted as recommending that the bit-mutation rate should be n^{-1} where n is the string length. The mutation rate is set to 20% based on this recommendation. If offspring are feasible with respect to the constraints, those are new chromosomes in the next search process for the placement of control points. We created five new chromosomes.

Although the placement of control points is fixed during choosing initial solutions randomly, the model searches for an optimum solution with GA changing the placement of control points as well as vertical distances at control points. A chromosome (a single solution) contains information on the placement of control points. Similarly, the crossover and a random mutation are applied. Five new feasible offspring are created for new chromosomes in the next generation. We repeat this process for 10 000 generations (iterations).

After the best solution has been found from the above procedure, the genetic algorithm shown in Fig. 3 is again applied in order to intensify the search in the region of the best solution. In this second search process, five feasible solutions are generated for initial solution again by changing alternative height at control points randomly at intervals of 10 cm within 1 m above and below the best path. After generating the initial solutions, crossover and mutation of vertical heights at control points are carried out while the placement of control points is fixed. This second process stops after 1000 iterations.

Tabu search

Tabu search is a recently developed solution strategy for combinatorial optimization problems (Glover 1989) and has evolved from gradient search techniques (Glover and Laguna 1993). Gradient search techniques can guarantee an optimal solution when the solution space is convex. However, some real-world combinatorial problems do not have a convex solution space, and others are also discrete. Tabu search can systematically look for feasible solutions to both discrete and non-convex problems. The key to Tabu search is that it remembers the choices it makes, thereby avoiding becoming trapped in local optima, a feature not common to traditional gradient search algorithms. This forces the exploration of other areas of the solution space, thus increasing the chance of locating a good solution. Tabu search has been successfully applied to a number of important problems. Within forestry, it has been used in developing plans with spatial habitat requirements for elk (Bettinger et al. 1997) and aquatic habitats (Bettinger et al. 1998), and optimizing stand harvest and road construction schedules (Richards and Gunn 2000).

In this process, while the placement and the number of control points are fixed, we generate a set of five feasible solutions changing heights at control points at intervals of 1 m within 10 m above and below ground height randomly (Fig. 4). Then, the best solution is used for Tabu search. The Tabu list is developed to keep track of choices which have been recently made. In the first iteration, the Tabu values in the Tabu list are all zero.

$$\text{height}(0,-1,2,6,-9,4)$$
$$\text{Tabu list} = (0,0,0,0,0,0)$$

For each successive iteration of the model, a neighborhood, which is a set of new feasible solutions, is created by slightly changing the previous feasible solution. In our model, a neighborhood is:

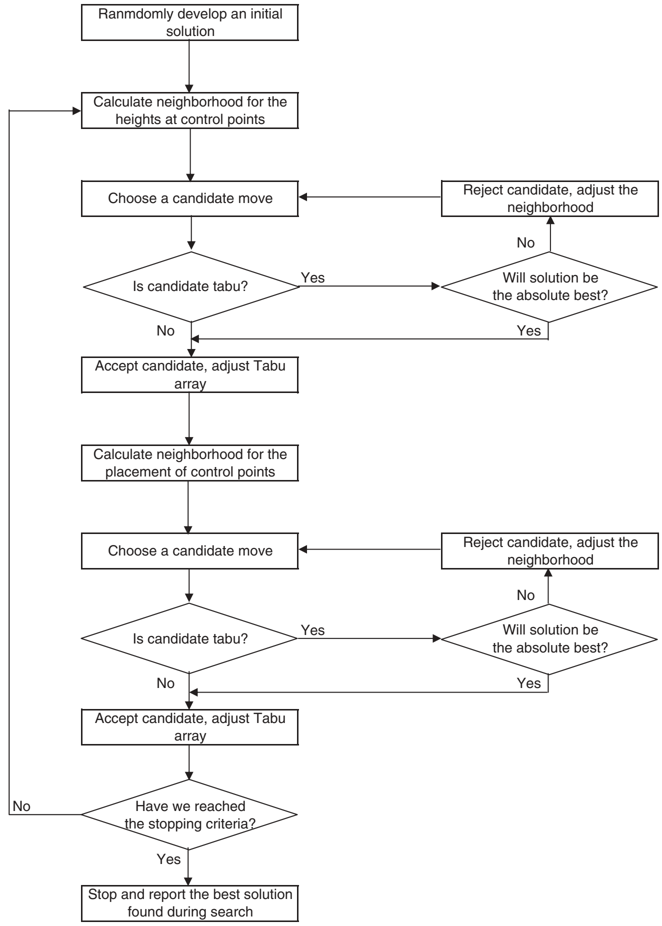

Fig. 4. A flow chart of the Tabu search process

$$(0,-10,2,7,-9,4),(0,-9,2,7,-9,4),\cdots(0,10,2,7,-9,4)$$
$$(0,-1,-10,7,-9,4),(0,-1,-9,7,-9,4),\cdots(0,-1,10,7,-9,4)$$
$$(0,-1,2,-10,-9,4),(0,-1,2,-9,-9,4),\cdots(0,-1,2,10,-9,4)$$
$$(0,-1,2,7,-10,4),(0,-1,2,7,-8,4),\cdots(0,-1,2,7,10,4)$$
$$(0,-1,2,7,-9,-10),(0,-1,2,7,-9,-9),\cdots(0,-1,2,7,-9,10)$$

Tabu Search selects candidate decision choices from a neighborhood.

If the candidate decision choice is Tabu (has been selected previously), it can be rejected from consideration, and another candidate is selected. Rules, called aspiration criteria, can be set to allow consideration of candidate choices that are Tabu. Aspiration criteria allow further consideration of Tabu candidate choices if the inclusion of the choice in the current solution will result in a solution that has an objective function value which is better than any previously observed objective function value. If a choice is not Tabu, it is then evaluated for feasibility with respect to requirements. If the inclusion of the candidate choice in the solution will violate feasibility, the candidate choice is rejected. Feasibility is maintained at all times, thus strategic oscillation is not used here (Richards and Gunn 2000).

Table 1. Best average solutions of six optimization approaches and heights at control points without changing the placement of the control points

	Start point	Control point				End point	Best cost ($/m)	Average cost ($/m)
		7	10	12	15			
Manual design	0.00	−0.34	0.91	0.70	−0.41	0.00	269.57	
Global optimum solution	0.0	−0.5	0.9	0.0	−1.0	1.3	237.93	
Genetic algorithm	0.0	−0.5	0.8	0.0	−1.0	0.8	238.46	247.27
Tabu search	0.0	−0.5	0.9	0.0	−1.5	1.7	245.75	261.86

If the inclusion of the candidate choice does not violate feasibility with respect to the requirements, the candidate choice is formally brought into the solution, and the resulting solution's objective function value is compared against the best previously observed objective function value (stored in memory). If the resulting solution is better than the previous best solution, it is saved as the best solution. The algorithm moves forward one iteration with the inclusion of the candidate choice in the solution. If the resulting solution is not better than the previous best solution, the algorithm moves with the candidate that will produce the maximum positive gain in the objective function value. If a positive gain is not possible, the algorithm moves with the candidate that will produce the least decline in the objective function value. Thus the search is not constrained at local optima.

If the change of the second control point from 2 to 9 is feasible with respect to the constraints and represents the best possible improvement in the objective function value or the least deterioration of the objective function value, it is given the Tabu value 3.

$$\text{height}(0,-1,9,7,-9,4)$$
$$\text{Tabu list} = (0,0,3,0,0,0)$$

After each subsequent iteration of the model, the Tabu value is decreased by one. When the Tabu value equals zero once again, the second control point is not considered Tabu, and will not be subject to the Tabu restriction.

Although the placement of control points is fixed during choosing initial solutions, the placement of control points changes during Tabu search:

$$\text{placement}(0,7,10,12,15,18)$$
$$\text{Tabu list} = (0,0,0,0,0,0)$$

If the change of the first control point from 7 to 3 is formally accepted into the solution, the Tabu value for the first control point is set to 15 in this study. A new neighborhood is then created, and the search process continues. This process ends when 1000 iterations have occurred.

After the best solution is found from the above procedure, we intensify the search in the region of the best solution. The Tabu search shown in Fig. 4 is carried out for vertical heights at control points again at intervals of 10 cm within 1 m above and below the best path in order to decide the final best path while the placement of control points is fixed. This second search process ends when 100 iterations have occurred.

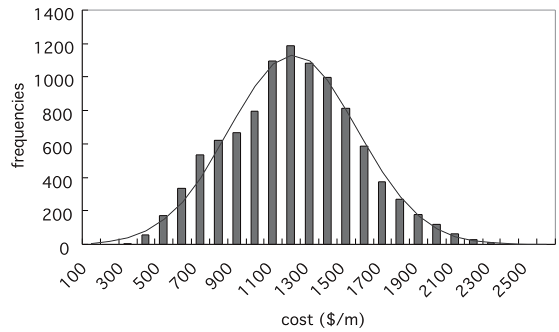

Fig. 5. The fitted normal distribution of the randomly generated solutions without changing the placement of control points

Results and discussion

Optimization of vertical alignments without changing the placement of control points

The model was developed with Microsoft Visual C++ on a desktop computer under Windows 2000. Six optimization approaches were conducted for each condition. First, we optimized vertical alignments without changing the placement of control points. In these analyses, we conducted 1000 iterations for both the first and second GA process and 100 iterations for both the first and second TS process. In order to examine the quality of the solutions found by GA and TS, we found the global optimum solution by complete enumeration of all alternatives. This required about 87 h. The cost of the global optimum solution, $237.93/m was less than that found manually, $269.57/m (Table 1).

We also generated 10 000 feasible solutions randomly for a random sample in order to examine the quality of the solutions found by GA and TS. While the program generated 10 000 feasible solutions, the program also generated about 12 million unfeasible solutions. This indicated that it was hard to find feasible solutions for this problem. The average cost was $1160.82/m, the best was $249.21/m, the worst was $2336.42/m, and the standard deviation was $352.22/m. We fitted a normal distribution to the feasible solutions for the random sample (Fig. 5). The distribution was checked with a χ^2 test. Since the sample was randomly

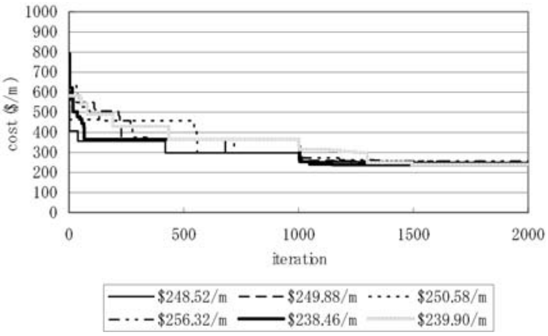

Fig. 6. Lowest cost found by GA without changing the placement of control points (search interval is 1 m before iteration 1000 and search interval is 0.1 m after iteration 1000)

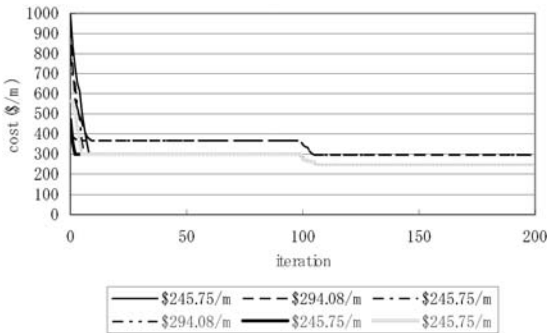

Fig. 7. Lowest cost found by TS without changing the placement of control points (search interval is 1 m before iteration 100 and search interval is 0.1 m after iteration 100)

generated, the fitted distribution should approximate the actual distribution for all possible solutions in the search space. If the distribution of all possible feasible solutions is assumed to be normally distributed with a mean and variance derived from the random sample, then we can say that the global optimum solution of $237.93/m was better than 99.57% of all possible feasible solutions. In other words, the probability of finding a solution that is less than $237.93/m is 0.43%. The solution value found manually was superior to 99.44% of the solutions in the distribution. We assume this high achievement is due to the designer's knowledge and experience.

Average and best costs found by GA were $247.27/m and $238.46/m, respectively, while average and best costs found by TS were $261.86/m and $245.75/m, respectively (Table 1). The best solution found by GA was almost the same as the global optimum solution. Six solutions found by GA were less than that found manually (Fig. 6). On the other hand, solutions found by TS seemed to be entrapped in two local optimum solutions (Fig. 7). One was $245.75/m and another was $294.08/m, which was worse than that found manually. However, a solution value of $294.08/m was still quite good, surpassing 99.31% of the possible feasible solutions. Therefore, we could say that both GA and TS found "good" solutions. If strategic oscillation was used to search between feasible and unfeasible regions in TS, it might find

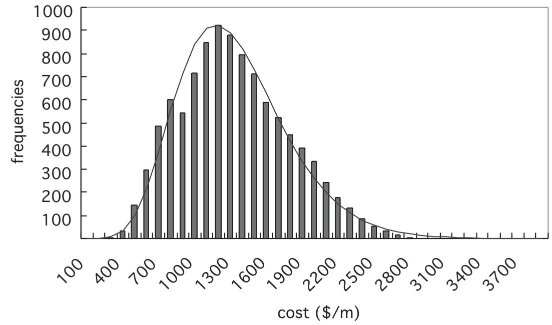

Fig. 8. The fitted gamma distribution of the randomly generated solutions by changing the placement of control points

a better solution than that found by TS tested in this study (Richards and Gunn 2000).

According to computational time, TS took about 40 min and GA took about 50 min for each search. GA was gradually reaching toward the optimum solution during the search, as GA uses random numbers (Fig. 6). On the other hand, Fig. 7 shows that the cost was rapidly decreasing during the TS process. This indicated that we could use a smaller number of iterations to reduce the computational time in the TS process. While GA was a powerful tool for finding a near-optimal solution, TS might be more useful for a large-scale problem due to its shorter solution time.

Optimization of vertical alignments by changing the placement of control points

We tried to optimize the profile by changing the placement of control points as well as the heights at control points. In this case, it was not possible to search all alternatives and find the global optimum solution within a reasonable time. Therefore, we only examined the probability of the results found by GA and TS by comparing with a random sample. We randomly generated 10 000 feasible solutions again by changing the placement of control points. In this case, the program generated about 20 million unfeasible solutions. Therefore, this problem was harder for the program to find feasible solutions than the previous problem in which the solutions were generated without changing the placement of control points. We fitted a gamma distribution to the feasible solutions for the random sample (Fig. 8). The distribution was checked with a χ^2 test. The average cost was $1288.29/m, the best was $267.92/m, the worst $2968.73/m, and the standard deviation was $454.80/m.

GA ($152.41/m) and TS ($180.59/m) both found a solution with a minimum cost, lower than that without changing the placement of control points ($237.93/m), while the minimum, maximum, and average values of the random sample in this problem were worse than those found in the previous problem (Table 2). Assuming the gamma distribution for the random sample, the probability of finding a solution better than the best value found by GA and TS was less than 0.01%. According to computational time, GA and TS took about 7 h and 2 h, respectively. Although we could not

Table 2. Best and average costs ($/m) of six optimization approaches with different numbers of control points

Number of control points		3	4	5
Genetic algorithm	Best	200.70	152.41	135.17
	Average	233.66	166.97	148.24
Tabu search	Best	212.48	180.59	127.14
	Average	258.32	207.51	141.45

Table 3. Costs for each element ($/m)

Element	Sub-element	Manual design	Best solution
Staking		1.22	1.22
Clearing and grubbing		8.52	9.05
Earthwork allocation		8.14	8.12
Concrete block		232.72	89.14
Surfacing	Base course	6.19	6.20
	Traction surface	3.25	3.53
Watering	Excavation	0.99	0.97
	Surfacing	1.81	1.83
Seeding and mulching		0.84	1.03
Drainage and riprap	Culvert	0.44	0.44
	Riprap	0.02	0.02
Maintenance		5.43	5.59
Total		269.57	127.14

examine how close to the global optimum solution these solutions were, it was clear that both GA and TS found "good" solutions within a reasonable time. While GA could find the better solution by spending more time than TS, TS found a good solution in less time. Coding skill, fine-tuning of algorithms, and testing of parameters are different between GA and TS. However, this trend of the difference between GA and TS is similar to the result without changing the placement of control points.

Next, we examined the effect of the number of control points on construction cost. We conducted searches with three and five control points (Table 2). Even though the number of control points was reduced from four to three, the best value found by GA and TS with changing the placement of three control points was less than that without changing the placement of four control points. Therefore, it is important to examine the placement of control points. However, it is hard to examine all control point placements manually. So, this method might be helpful for a designer to decide the forest road profile. When the number of control points was increased from four to five, TS found a better solution than GA and any other solutions found in this study. The best solution found by TS with five control points, $127.14/m, was less than half of manually designed value, $269.57/m (Table 2, Fig. 1); 86% of total costs designed manually were concrete block costs (Table 3). The Tabu search successfully optimized vertical alignments which reduced concrete block costs and total costs to $89.14/m and $127.14/m, respectively. Moreover, the amount of material moved from the borrow area was reduced from 73.94 to 0.94 m^3. As a result, the model was able to balance fill and cut volumes in this section.

Conclusions

In this study, we tested two methods used to design a forest road profile using the genetic algorithm and Tabu search heuristic techniques to minimize construction plus maintenance costs. The results indicated that both GA and TS found "good" solutions within a reasonable time. Because it is not possible to evaluate many alternatives manually, this model is helpful for a designer. While GA found a better solution than TS, TS found a good solution in less time. Therefore, a hybrid method, using TS first and then using GA, might find a better solution in less time than a single method using either GA or TS.

If the number of control points was increased, the construction cost would be reduced because the forest road profile would become closer to the ground profile and the earthwork volume would then be reduced. However, driving safety and comfort might be decreased when the gradients changed at more points. We should consider the trade-offs between the economic aspect of roads and other road design considerations such as the driver's comfort in the future work.

In the future, we expect that forest roads will be designed using data from a high-resolution DEM from LIDAR, if LIDAR becomes more common and its accuracy increases. In this model, earthwork volume was calculated using the average end-area method. This method is suitable only for application to level terrain. This model would be more accurate using LIDAR and by incorporating methods of calculating the earthwork volume which are more suitable for hilly and mountainous terrain (Easa 1992).

Literature cited

Akay A (2003) Minimizing total cost of construction, maintenance, and transportation costs with computer-aided forest road design. Ph.D. thesis, Oregon State University, Corvallis, USA

Antoniotti P (1969) APPOLLONL: a new road design optimization procedure. In: PTRC symposium on cost models and optimization in road location, design and construction, London, pp 236–241

Antonisse (1989) A new interpretation of schema notation that overturns the binary encoding constraint. In: Proceedings of the 3rd international conference on genetic algorithms. Morgan Kaufmann, Los Altos, CA, USA

Bettinger P, Sessions J, Boston K (1997) Using Tabu search to schedule timber harvests subject to spatial wildlife goals for big game. Ecol Model 94:111–123

Bettinger P, Sessions J, Johnson KN (1998) Ensuring the compatibility of aquatic habitat and commodity production goals in eastern Oregon with a Tabu search procedure. For Sci 44:96–112

Boise Cascade Corporation (1999) SEDMODL-Boise Cascade road erosion delivery model. Technical Documentation

De Jong KA (1975) An analysis of the behavior of a class of genetic adaptive systems. Doctoral dissertation, University of Michigan, USA

Dowsland KA (1993) Simulated annealing. In: Reeves C (ed) Modern heuristic techniques for combinatorial problems. Wiley, New York, pp 20–69

Easa SM (1992) Estimating earthwork volumes of curved roadways: mathematical model. J Transport Eng 118:834–849

Glover F (1989) Tabu search. Part I. ORSA J Comput 1:190–206

Glover F, Laguna M (1993) Tabu search. In: Reeves C (ed) Modern heuristic techniques for combinatorial problems. Wiley, New York, pp 70–150

Goldberg DE (1989) Genetic algorithms in search, optimization, and machine learning. Addison-Wesley, Reading, MA, USA

Ichihara K, Tanaka T, Sawaguchi I, Umeda S, Toyokawa K (1996) The method for designing the profile of forest roads supported by genetic algorithm. J For Res 1:45–49

Kanzaki K (1973) On the decision of profile line of forest road by dynamic programming (in Japanese). J Jpn For Soc 55:144–148

Klemperer D (1996) Forest resource economics and finance. McGraw-Hill, New York

Kramer BW (2001) Forest road contracting, construction, and maintenance for small forest woodland owners. Oregon State University, Forest Research Laboratory, Research Contribution 35

Mayer R, Stark R (1981) Earthmoving logistics. J Const Div 107(CO2):297–312

Mannering FL (1990) Principles of highway engineering and traffic analysis. Wiley, New York

Nicholson AJ (1976) A variational approach to optimal route location. J Highway Eng 23:22–25

O'Brien WT, Bennett DW (1969) A dynamic programming approach to optimal route location. In: Proceedings of a symposium on construction models and optimization in road location, design and construction. London, pp 175–199

Reeves C (1993) Genetic algorithms. In: Reeves C (eds) Modern heuristic techniques for combinatorial problems. Wiley, New York, pp 151–196

Reutebuch SE, Ahmed KM, Curtis TA, Petermann D, Wellander M, Froslie M (2000) A test of airborne laser mapping under varying forest canopy. In: Proceedings of the ASPRS 2000 Annual Conference, 22–26 May 2000, Washington, D.C. American Society for Photogrammetry and Remote Sensing, Bethesda, MD

Richards EW, Gunn EA (2000) A model and Tabu search method to optimize stand harvest and road construction schedules. For Sci 46:188–203

Smith DK (1982) Network optimization practice: a computational guide. Ellis Horwood, West Sussex, pp 55–65

Suzuki H, Ichihara K, Noda I (1998) Road planning in forest for recreation. J Jpn For Eng Soc 13:151–160

Trietsch D (1987) A family of methods for preliminary highway alignment. Transport Sci 21:17–25

USDA Forest Service (1999) Cost estimating guide for road construction: Region 6, Portland