A PSO based Approach to Assign Segments for Reducing Excavated Soil in Shield Tunneling

Koya Ihara[1], Shohei Kato[1,2], Takehiko Nakaya[3], Tomoaki Ogi[3] and Hiroichi Masuda[3]

[1]*Dept. of Computer Science and Engineering, Graduate School of Engineering, Nagoya Institute of Technology, Gokiso-cho, Showa-ku, Nagoya 466-8555, Japan*

[2]*Frontier Research Institute for Information Science, Nagoya Institute of Technology, Gokiso-cho, Showa-ku, Nagoya 466-8555, Japan*

[3]*Shimizu Corporation, 2-16-1 Kyobashi, Chuo-ku, Tokyo 104-8370, Japan*

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Abstract: It is expected that artificial intelligence reduces labor and improves productivity of the shield tunneling, which is one of tunnel construction methods. In a planning process of the shield tunneling, segments of a tunnel are assigned along to a predetermined curve called the planning line. Conventionally, skilled engineers manually assign the segments to minimize gaps between each segment and the planning line. Nevertheless, we have only to reduce each gap less than a tolerance, and there is a demand to reduce the amount of soil excavated along to the segments. Handling the reducing gaps as constraints and reducing the amount of excavated soil as an objective, this paper addresses the segment assignment as a constrained combinatorial optimization problem. These constraints are severe, and the problem has an extremely narrow feasible region. For this problem, we proposed the ε constrained integer categorical particle swarm optimization (εICPSO), adapting a constraint handling method called the ε constrained method to the integer categorical particle swarm optimization. The effectiveness of the εICPSO to the segment assignment is shown by the two-dimensional simulator experiment using real construction data. The experimental results show that the proposed method has a potential to reduce the amount of excavated soil as compared to the conventional method (skilled engineer) while keeping the all gaps between segments and the planning line falling within the tolerance. The εICPSO statistically performed the best in all the test problems.

1 INTRODUCTION

In the construction industry of all over the world, manpower shortage is serious problem. Windapo, A. O. reported that a skilled labor shortage is preponderant and it contributes to a decrease in productivity and product quality in the South African construction industry (Windapo, 2016).

The Japanese construction industry also has problems: manpower shortage, ageing workers, and decrease in international competitiveness. Since November 2015, the Japanese Ministry of Land, Infrastructure, Transport and Tourism (MLIT) has been promoted the *i-Construction* (Suzuki, 2016), an effort aiming to optimize and upgrade the whole process from investigation and design, construction and inspection, up to maintenance. Its major concepts are utilization of information and communication technology and introducing innovative technology such as artificial intelligence (AI) by cooperation between industries, governments, and academia. Our research aims to develop a practical construction support system according to the i-Construction.

The *shield tunneling* (Maidl et al., 2013; Japan Society of Civil Engineers, 2007) is a tunnel construction method used around the globe. It is necessary to construct tunnels under sever conditions such as urban areas. In the civil engineering and mechanical engineering domains, the shield tunneling techniques have been studied intensively (Koyama, 2003). There are also a few studies (Suwansawat and Einstein, 2006; Hasanipanah et al., 2016) about shield tunneling in artificial intelligence domain. However no studies have focused planning processes of shield tunneling. In the planning process, segments of the tunnel are assigned along to the predetermined planning line, where the tunnel is expected to be constructed. Conventionally, skilled engineers manually assign the segments to minimize gaps between each segment and the planning line. Nevertheless, we have only to reduce each gap less than a tolerance, and there is a demand to reduce the amount of soil excavated along to the segments.

It is assume that automation and optimization of

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the segment assignment contribute to eliminate a skilled labor shortage and to improve productivity. This paper addresses the segment assignment as a constrained combinatorial optimization problem. This problem has severe constraints, and its feasible region is extremely narrow as compared with its large search space. For optimization problems having severe constraints, Takahama and Sakai proposed the ε constrained method (Takahama and Sakai, 2005). The ε constrained method is a method that adds the ability of constraint handling to the algorithms which was originally designed for unconstrained optimization problems. Although this method has been adapted to several continuous optimizations (Takahama and Sakai, 2010; Bonyadi et al., 2013; Yang et al., 2014), there is no report of adapting it to discrete optimizations. Adapting the ε constrained method to the Integer Categorical Particle Swarm Optimization (ICPSO) (Strasser et al., 2016), we propose ε constrained ICPSO (εICPSO) for constrained combinatorial optimization. We attempt to verify the effectiveness of the εICPSO to segment assignment through the two-dimensional simulation experiment using real construction data.

2 RELATED WORK

There are studies of adapting the ε constrained method to metaheuristics algorithms, e.g., particle swarm optimization (PSO) (Kennedy, 2011), differential evolution (DE) (Storn and Price, 1997), multiobjective evolutionary algorithm based on decomposition (MOEA/D) (Zhang and Li, 2007), and so on. Takahama and Sakai proposed an ε constrained differential evolution (εDE) (Takahama and Sakai, 2006), and its extended version using an archive (Takahama and Sakai, 2010). Takahama and Sakai proposed an ε constrained particle swarm optimizer (εPSO) (Takahama and Sakai, 2005). Bonyadi, Li, and Michalewicz proposed the hybrid method of εPSO and an other constraint handling method (Bonyadi et al., 2013). Yang, Cai, and Fan introduced the ε constrained method into MOEA/D in order to extend it for constrained multiobjective optimization problems (Yang et al., 2014). All of these methods are applicable to only continuous optimization problems. Few researches have reported on discrete constrained optimization methods adapting the ε constrained method.

3 SEGMENT ASSIGNMENT

In this section, we explain the segment assignment and its formulation as constrained combinatorial optimization problem.

3.1 Shield Tunneling

The *shield tunneling* is a tunnel construction method using excavation machines called *shield machines* shown in Figure 1. The front surface of the shield machine has cutters, called the *cutter head*, to excavate grounds. The *over cut*, which is the external cutter equipped outside of the front surface, is controlled so that the machine body can pass without contacting to ground wall. A shield machines is divided to a *front drum* and a *rear drum*. The angle between the front drum and the rear drum, called *joint angle*, is controlled for the shield machine to go around curves. Segments are assembled at the rear of the shield machine. The shield machine is propelled by the reaction force given from its jack pushing the located segment.

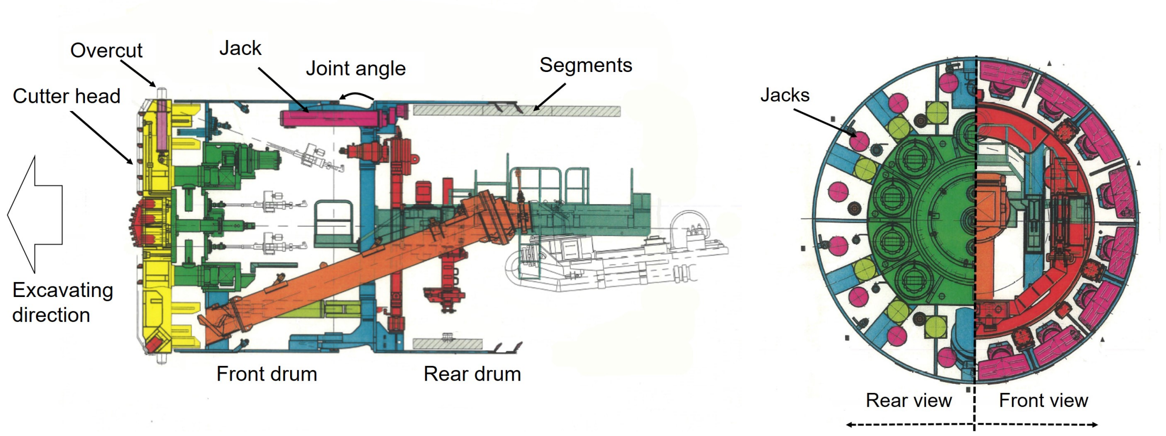
3.2 Segment Assignment Problem

In planning process, multiple types of segments are provided for each construction and they are assigned along to the planning line consisting of straight lines and curves so that the gaps between each segment and the planning line fall within a tolerance as shown in Figure 2. Conventionally, skilled engineers manually assign segments in order to minimize gaps without considering construction costs. However, because this assignment roughly determine the excavation route of shield machine, it is assumed that optimization of this assignment reduce shield construction costs. Thus we focus on the segments assignment problems for reducing the amount of excavated soil.

There are following two demands in the segment assignment. (1) To make the gaps between each segment and the planning line fall within the tolerance. (2) To reduce the amount of soil excavated according to the segments by the shield machine. In this paper, the former is treated as an inequality constraint, and the latter is treated as an objective function. We define segment assignment as the following constrained combinatorial optimization problem.

$$\begin{aligned} \text{minimize} \quad & f(\boldsymbol{x}), \\ \text{subject to} \quad & (g_i(\boldsymbol{x}) - g_t) \leq 0, \\ & x_i \in \{1, \cdots, k\}, \quad (i = 0, \cdots, n) \end{aligned} \tag{1}$$

where $x_i \in \{1, \cdots, k\}$ corresponds to the type of the segment assigned to i-th position, and k is the number of types. A decision variable vector $\boldsymbol{x} =$



(a) Side View (b) Rear and Front View

Figure 1: An Example of Construction Diagrams of A Shield Machine.

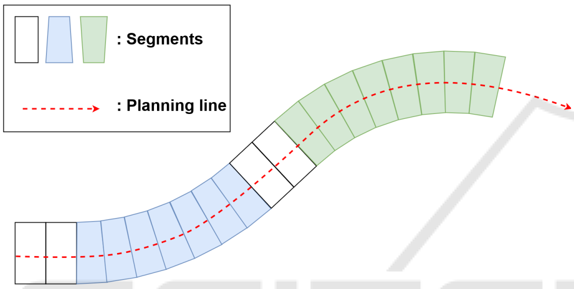


Figure 2: An Example of Segment Assignment.

$(x_1, x_2, \cdots x_n)$ expresses the assigned segments. The objective function $f(\boldsymbol{x})$ is the amount of soil excavated along to segments $\boldsymbol{x}$ by the shield machine; $g_i(\boldsymbol{x})$ as the gap between the i-th segment and the planning line; and g_t is the gap tolerance.

This problem has n-dimensional decision variable vector, and n is generally over several hundreds. The problem has an extremely large search space. However, it is required to earn a solution in a short time, because the segment assignment plan is should be recreated when the practical construction deviates from the plan. Population-based metaheuristics, such as swarm intelligence (SI), is often used for optimization problems in the real-world because of its ease of parallelization and efficiency of its multi-point search (Hassanien and Emary, 2018; Soares et al., 2016; Zhang et al., 2014; Glover and Kochenberger, 2006). Although there are many discrete optimization algorithms based on SI, they often only consider integer problems (Kennedy and Eberhart, 1995; Pampara et al., 2005). The segment assignment has variables whose values are not numerical but categorical and unordered. The PSO is one of the most widely used algorithm belonging to SI. Integer Categorical PSO (ICPSO), presented in (Strasser et al., 2016), outperformed other discrete versions of PSO in unordered discrete optimization. In addition, the gap tolerance g_t is commonly about 50 mm, whereas the diameter of segments is around 10 m. The segment assignment has n severe constraints. For handling the severe constraints, the ε constrained method is proposed by (Takahama and Sakai, 2005). Thus, we adapt the ε constrained method to ICPSO for constrained combinatorial optimization.

4 PROPOSED METHOD

This section describes the considering constrained combinatorial optimization problems, ε constrained method, and εICPSO.

4.1 Problem Domain

In the proposed method, we consider the following constrained optimization problem.

$$
\begin{aligned}
\text{minimize} \quad & f(\boldsymbol{x}), \\
\text{subject to} \quad & g_j(\boldsymbol{x}) \le 0, \quad (j = 1, \cdots, q) \\
& h_j(\boldsymbol{x}) = 0, \quad (j = 1, \cdots, r) \\
& x_i \in \{l_i, \cdots, u_i\}, \ (i = 1, \cdots, n)
\end{aligned}
$$

where $\boldsymbol{x} = (x_1, \cdots, x_n)$ is an n-dimensional decision variable vector; $f(\boldsymbol{x})$ is a objective function; $g_j(\boldsymbol{x}) \le 0$ are q inequality constraints; and $h_j(\boldsymbol{x}) = 0$ are r equality constraints. $f(\boldsymbol{x})$, $g_j(\boldsymbol{x})$, and $h_j(\boldsymbol{x})$ are real-valued functions. The integer values l_i, and u_i are the lower and upper bounds of x_i respectively. The search space is defined by the lower and upper bounds; the feasible region is defined by the inequality and equality constraints.

4.2 ε Constrained Method

The ε constrained method (Takahama and Sakai, 2005) adds the ability of constraint handling to the algorithms originally designed for unconstrained optimization problems. This method introduces ε *level comparison*, which is a comparison operator considering both the constraints and objective values for ranking candidate solutions. In this method, constraint violation $\phi(\boldsymbol{x})$ is defined as a measure of how much constraints a solution violates. The constraint violation can be given by the maximum of all constraints of all constraints or the sum of all constraints.

$$\phi(\boldsymbol{x}) = \max\{\max_j\{0, g_j(\boldsymbol{x})\}, \max_j |h_j(\boldsymbol{x})|\},$$
$$\phi(\boldsymbol{x}) = \sum_j \max\{0, g_j(\boldsymbol{x})\}^p + \sum_j |h_j(\boldsymbol{x})|^p, \quad (2)$$

where p is a positive number. In this paper, constrain violation is given by (2), the sum of all constraints.

The ε level comparison ($<_\varepsilon$,$\leq_\varepsilon$) is defined as an order relation on the set of $(f(\boldsymbol{x}), \phi(\boldsymbol{x}))$. If $f_1(f_2)$ and $\phi_1(\phi_2)$ are the objective values and the constraint violation of solution point $x_1(x_2)$ respectively, then the comparison operators $<_\varepsilon$ and $\leq_\varepsilon$ are defined by the following:

$$(f_1, \phi_1) <_\varepsilon (f_2, \phi_2) \Leftrightarrow \begin{cases} f_1 < f_2, & (\phi_1, \phi_2 \leq \varepsilon) \\ f_1 < f_2, & (\phi_1 = \phi_2) \\ \phi_1 < \phi_2, & \text{otherwise} \end{cases}$$

$$(f_1, \phi_1) \leq_\varepsilon (f_2, \phi_2) \Leftrightarrow \begin{cases} f_1 \leq f_2, & (\phi_1, \phi_2 \leq \varepsilon) \\ f_1 \leq f_2, & (\phi_1 = \phi_2) \\ \phi_1 < \phi_2, & \text{otherwise} \end{cases}$$

This definition means that the ε level comparison compares two solutions by constraint violation value first. If both solutions have violation value under a small threshold ε the two solutions are then compared by the objective function value only.

4.3 εICPSO

The εICPSO is a constrained combinatorial optimization algorithm based on ICPSO with candidate solutions ranked by the ε level comparison. The ICPSO is a novel PSO algorithm that has been shown to surpass other discrete PSO algorithms (Strasser et al., 2016). In the PSO, particles search for the best position of the search space. Particles have a position and a velocity, and the position correspond to a candidate solution. Original PSO assumes continuous state variables. In the ICPSO, the representation of the particle's position is altered so that each attribute in a particle is a distribution over its possible values rather than a value itself similarly to Estimation of Distribution Algorithms (EDAs) (Larrañaga and Lozano, 2002). A particle is evaluated by sampling a candidate solution from these distributions and then calculating its fitness. In this subsection, the εICPSO is described in more detail.

In the εICPSO, a particle p's position $\mathbf{X}_p$ is represented as

$$\mathbf{X}_p = [\mathcal{D}_{p,1}, \mathcal{D}_{p,2}, \cdots, \mathcal{D}_{p,n}],$$

where each $\mathcal{D}_{p,i}$ is the probability distribution for variable X_i. In other words, each component of the position vector is a set of probabilities

$$\mathcal{D}_{p,i} = [d^a_{p,i}, d^b_{p,i}, \cdots, d^k_{p,i}],$$

where $d^j_{p,i}$ denotes the probability that variable X_i takes on value j for particle p. A particle p's velocity $\mathbf{V}_p$ is a vector of n vector φ, which control the particle's probability distributions.

$$\mathbf{V}_p = [\varphi_{p,1}, \varphi_{p,2}, \cdots, \varphi_{p,n}],$$
$$\varphi_{p,1} = [\psi^a_{p,i}, \psi^a_{p,i}, \cdots, \psi^a_{p,n}],$$

where $\psi^j_{p,i}$ corresponds to velocity of particle p for variable i in state j. The velocity and position update equations are applied directly to the values in the distribution.

$$\begin{aligned} \mathbf{V}_p =& \omega \mathbf{V}_p + U(0, \phi_1) \otimes (\mathbf{pBest} - \mathbf{X}_p) \\ & + U(0, \phi_2) \otimes (\mathbf{gBest} - \mathbf{X}_p), \\ \mathbf{X}_p =& \mathbf{X}_p + \mathbf{V}_p, \end{aligned}$$

where each operator is performed component-wise over each variable in the vector; and $U(0, \phi_1)$ and $U(0, \phi_2)$ are uniformly distributed random numbers between 0 and ϕ_1 and 0 and ϕ_2 respectively. The vector **pBest** is the best position in the search space this particle has ever reached; the **gBest** is the best position in the search space any particle in the swarm has ever reached. The particle moves in the search space by adding the updated velocity to the particle's position vector at the current iteration. The particle's behavior is controlled with adjusting the parameter ω, ϕ_1, and ϕ_2 known as inertia, the cognitive component and the social component.

After the velocity and position update, any value outside [0,1] is mapped to the nearest boundary in order to maintain a valid probability. In addition, the distribution is then normalized to ensure that its values sum to 1.

To evaluate a particle p, its distributions are sampled to create a candidate solution $\mathbf{S}_p = [s_{p,1}, s_{p,2}, \cdots, s_{p,n}]$ where $s_{p,j}$ denotes the state of variable X_j. The samples are evaluated by the fitness function, and then the distributions are evaluated by their own sample's fitness value.

When a sample produced by a particle exceed the global or local best in ε level comparison, the best values are updated using both the distribution from the particle position P_p and the sample itself $\mathbf{S}_p$. Formally, for all states $j \in Vals(X_i)$ the global best's probability is updated as

$$d^j_{gB,i} = \begin{cases} \varepsilon \times d^j_{p,i} & (j \neq s_{p,i}) \\ d^j_{p,i} + \sum_{\substack{k \in Vals(X_i) \\ \wedge k \neq j}} (1-\varepsilon) \times d^k_{p,i} & (j = s_{p,i}) \end{cases}$$

where ε, the *scaling factor*, is a user-controlled parameter that determines the magnitude of the shift in the distribution restricted to $[0,1)$, and $d^j_{gB,i}$ is the global best position's probability that variable X_i takes value j. This update increases the probability of the distribution producing samples similar to the best sample, while maintaining a valid probability distribution. In other words, it ensures that the best position's probability of producing a variable identical to the best sample's greater than $1-\varepsilon$which can be shown as follows:

$$\begin{aligned} d^k_{gB,i} &= d^k_{p,i} + \sum_{j \in S_v(X_i,k)} (1-\varepsilon) \times d^j_{p,i} \\ &= \varepsilon \times d^k_{p,i} + (1-\varepsilon) \times d^k_{p,i} + \sum_{j \in S_v(X_i,k)} (1-\varepsilon) \times d^j_{p,i} \\ &= \varepsilon \times d^k_{p,i} + (1-\varepsilon), \end{aligned}$$

where $S_v(X_i,k) = \{j | j \in Vals(X_i) \wedge j \neq k\}$ and $k = s_{p,i}$. The scaling factor should be controlled according to the dimension of the decision variable, since a large dimension increases the difference between the best sample and a sample expected to be produced by the updated distribution. The local best is updated in exactly the same way. At the end of the algorithm, the global best sample is returned as the solution.

5 EXPERIMENT

We attempt to verify the effectiveness of εICPSO to segment assignment through the two-dimensional simulation experiment using real construction data with comparison with the ε constrained genetic algorithm (εDGA) (Ihara et al., 2018). Candidate solutions (assigned segments) are evaluated by the two-dimensional simulator we developed. Solutions are encoded to particles and integer chromosome and they are evolved by the εICPSO and εDGA.

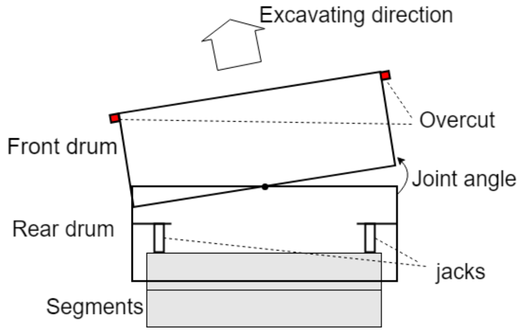


Figure 3: Model of Shield Machines in the Two-dimensional Simulator.

5.1 Two-dimensional Simulator for Segment Assignment

In the two-dimensional simulator, we consider the shield machines as shown in Figure 3. The simulator evaluates segments by the area of the region a shield machine passed along to the segments assuming that the amount of excavated soils is in proportion to the area. The area of the region through which the front of the shield machine passes is determined by the product of the width of the shield machine and the total length of the planning line. Thus, We define the area of the excavated field excluding this field as the fitness because this field does not depend on segment assignment. This fitness is equivalent to the amount of the soil excavated by the overcut.

5.2 Conventional Method

In the construction site, segments are manually assigned by skilled engineers. However it is difficult to compare with real skilled engineers' assignment, because engineers take a lot of time to assign segments in each problem. Since skilled engineers assign in order to minimize the gaps without considering the amount of excavated soil, their methods are approximately equivalent to the greedy method where segments are assigned to minimize gaps. Thus we compare the proposed methods to the greedy method instead of skilled engineers.

5.3 εDGA

For the segment assignment problem, Ihara *et al.* proposed the εDGA (Ihara et al., 2018), which is a combination of the ε constraint method and discrete genetic algorithm. The εDGA is basically based on standard genetic algorithms, but in the algorithm, individuals are ranked by the ε level comparison with

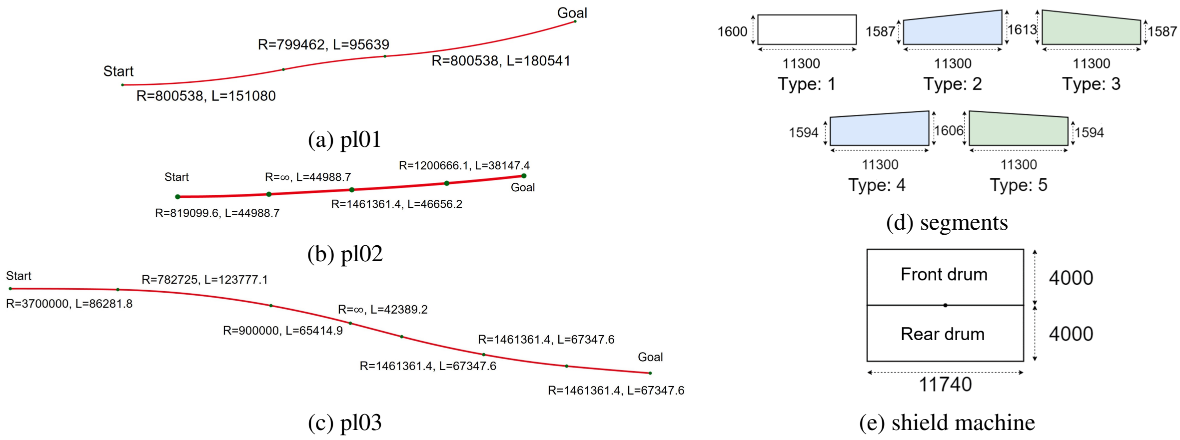


Figure 4: Dimensions [mm] of the planning lines, the segments, and the shield machine used in the experiments.

the ε level controlled in each generation. In particular, the parents are selected by selection methods based on comparison of individuals such as tournament selection (Miller et al., 1995) and ranking selection (Goldberg and Deb, 1991) using the ε level comparison instead of general comparison. Elite individuals are also selected by ε level comparison to carry over to the next generation according to elitism. The flow of the method is shown as follows:

1. Initialization: initial population is generated by randomness or heuristics with population size of N.
2. Determining terminate or not: If the termination conditions satisfy, this algorithm terminates. In this paper, the algorithm ends in the Tth generations.
3. Controlling the ε level: the feasible region is temporarily expanded by controlling the ε level. It is desirable that ε level decrease as generations go by.
4. Parents selection: individuals are ranked by ε level comparison, and selected by selection methods only based on ranking solutions to insert into a mating pool.
5. Crossover: crossover operators are applied to parents picked from the mating pool in order.
6. Mutation: when offspring are produced, each offspring has chance of mutation.
7. Replacement: N_e elite individuals are selected to carry out to the next generation instead of N_e worst offspring selected by the ε level comparison.
8. Return to step 2.

5.4 Initialization

In the constrained optimization problem, it is desirable search starts from in or near its feasible region, especially when the feasible region is narrow. A feasible solution can be found easily by the greedy method in the segment assignment as noted above. This experiment uses the feasible solution discovered by the greedy method for initializations. The εICPSO randomly initialized velocity and position vectors, then assuming that the feasible solution is earned by sampling a particle p's position, the p's local best and the global best are updated. In the εDGA initial individuals are created by the applying the uniform mutation to the feasible solution.

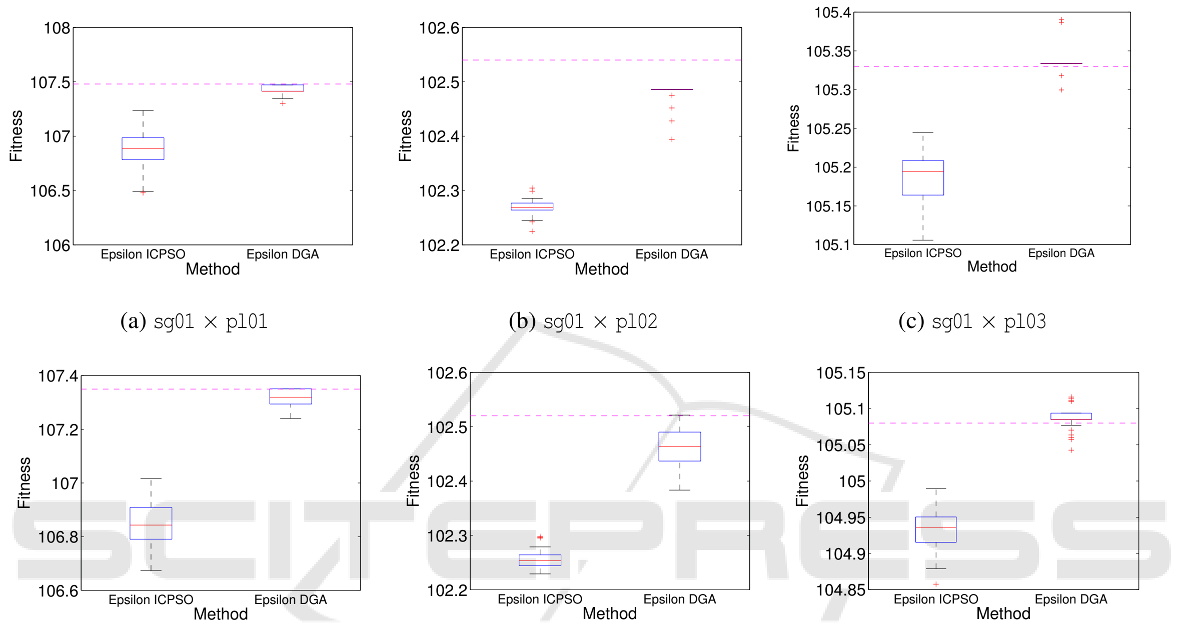
5.5 Experimental Setup

The algorithms tackle the constrained combinatorial optimization problem defined in (1). Planning lines are defined by the given series of curvature radius R and length L. Figure 4a, 4b, and 4c show the planning lines used in the experiment `pl01`, `pl02`, and `pl03`. The segments are defined as shown in Figure 4d, and we use the segment sets `sg01` and `sg02`, which include segments whose type number is from one to three, and from one to five, respectively. The gap tolerance g_t is set to 50 mm in each problem.

We conduct 50 trials of evolutions where fitness evaluations are limited up to 500,000 times with both the εICPSO and εDGA. The εICPSO uses a swarm of size 100, and the swarm is evolved for 5,000 iterations, owing to the recommendation of (Engelbrecht, 2014), which demonstrated that a large swarm may, counterintuitively, have difficulty exploring the search space. The cognitive component ϕ_1 and social component ϕ_2 are set to 1.49618, and the inertia ω is 0.729, which has been found to encourage convergent

Table 1: Experimental Result [m^2]50trials.

Problem		Skilled engineer	εICPSO			εDGA		
Segment set	Planning line	(greedy method)	average	best	worst	average	best	worst
sg01 ($k=3$)	pl01 (n=267)	107.48	**106.87**	106.47	107.23	107.42	107.30	107.47
	pl02 (n=210)	102.54	**102.26**	102.22	102.30	102.47	102.39	102.48
	pl03 (n=325)	105.33	**105.18**	105.10	105.24	105.33	105.30	105.39
sg02 ($k=5$)	pl01 (n=267)	107.35	**106.84**	106.67	107.01	107.32	107.24	107.35
	pl02 (n=210)	102.52	**102.25**	102.22	102.29	102.46	102.38	102.52
	pl03 (n=325)	105.08	**104.93**	104.85	104.99	105.08	105.04	105.11



(a) sg01 × pl01 (b) sg01 × pl02 (c) sg01 × pl03

(d) sg02 × pl01 (e) sg02 × pl02 (f) sg02 × pl03

Figure 5: Box plots of fitness scores of the εDGA and εICPSO for each problem with 50 trials, with horizontal dashed lines representing the conventional method's evaluations.

trajectories (Eberhart and Shi, 2000). In the pl01 and pl02 problems, the scaling factor $\varepsilon = 5.0 \times 10^{-4}$, and in the pl03 problems, $\varepsilon = 1.0 \times 10^{-4}$, due to large dimensions of the problems. In the εDGA, populations are evolved for 500 generations, with a population of size 1,000. Uniform crossover (Syswerda, 1989) is applied 95% of the time offspring are produced, and each offspring does uniform mutation (Goldberg, 1989) where each gene has a 5% chance of change to random value. Through the evolutions, ε level is set to 0.

5.6 Experimental Results

The experimental results show that the proposed method have a potential to find the segment assignment reducing the amount of excavated soil as compared to the conventional method (skilled engineer) while keeping the all gaps between segments and the planning line falling within the tolerance. Table 1 shows the experimental results on the problems (Figure 4). In the table, "average", "best", and "worst" are the average value, the best value, and the worst value of 50 trials on the each problem respectively. Bold values indicate algorithms that statistically significantly outperformed all other methods (paired Student t-Test, $\alpha = 0.01$). Figure 5 illustrates the performance of the εICPSO and εDGA. Their fitness scores are shown as box plots, where the boxes represent the 25th to 75th percentiles, the lines within the boxes represent the median, and the lines outside the boxes represent the minimum and maximum values. The conventional method's scores are represented by the horizontal dashed lines.

It is clear that the εICPSO has clear advantage over the εDGA. In all the problems, the εICPSO statistically performs the best. In particular, the worst scores of εICPSO exceed the εDGA's best and the skilled engineer's score. In complex problems, with large n or k, the difference in the performance is especially remarkable. Although the εDGA has potential to find the solution superior to the skilled engineer in terms of the best score, the its score averagely almost equivalent and at worst inferior in the `pl03` problems.

6 CONCLUSION

We addressed the segment assignment in shield tunneling as a constrained combinatorial optimization problem. This paper proposed the εICPSO and demonstrated its effectiveness to segment assignment problems. The experimental results showed its potential to reduce construction costs as compared with the conventional method. In all the test problems, the proposed method outperformed all the comparative methods. In the future, we will make more experiments using three-dimensional simulator for more accurate evaluation of the proposed method.

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