Research Paper

GA-based Design Tool for Piping Route Path Planning

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A genetic algorithm (GA) approach to support collaborative and interactive planning of a piping route path in plant layout design is presented. To present this approach, the paper mainly describes the basic ideas used in the methodology, which include the definition of genes to deal with pipe routes, the concept of spatial potential energy, the method of generating initial individuals for GA optimization, the zone concept in route generation using GAs, the evaluation of crossover methods, and definition and application of fitness functions. In order to apply the method to actual problems and to solve them in a practical manner, the study employs various heuristics, which are concept of direction, generation of initial individuals using intermediate point, extended two-points crossover, and dynamic selection. Those heuristics are also described and their effectiveness in the method is discussed. Then, the paper presents a prototype system that has been developed based on the methodology as a GA-based design tool for piping route path planning, and discusses the validity of the proposed method.

1. Introduction

Layout designs, which effectively utilize the functionality of component equipments and appropriately satisfy the spatial constraints, are playing a key role in engineering designs of various production systems, chemical plants, power plants, factories, etc. For piping design [9] as one of these layout designs, a designer initially creates an appropriate design model and interactively modifies the model in a trial-and-error manner until the final completion of an approved design.

Since there are so many things to consider from various perspectives, piping designs, therefore, are a difficult and time consuming task. First of all, it is very important to determine the appropriate flow speed from economic sense of view. The inner diameter of piping can be calculated based on the flow speed to minimize the overall pressure losses. In plant piping designs, pipings are categorized to several classes: process lines for insides of equipments, yard lines for outside of equipments and utility lines for water, steam and fuels. Pipings of the same categories in plant pipings should be arranged to be placed together. From the view point of mechanical design, on the other hand, pipings are categorized differently, namely, in terms of the place to be installed: on the ground, in the air and under the ground. Maintenance is also another important factor to be considered in designing a pipe route. Although piping should be accessed easily for maintenance, but they should not be placed on the walk way. Equipments should be placed in such a way as pipings are placed in parallel or rectangular, basically avoiding an diagonal path. Each supporting should possess the durability to support the pipings. For example, materials of the supporting should have good heat resistance so that they can minimize shape deformation.

One of the most difficult part in piping design would be to conduct pipe route planning, which is to design the appropriate route for piping connecting the starting and goal points. If the optimal pipe route is designed, it could be said that the most difficult part of piping design is completed. But it is very difficult even for a skilled designer to design the optimal pipe route especially under very complicated spatial constraints, which is just like going through a labyrinth, while keeping an appropriate space between the pipe and the surrounding walls or the equipments metaphorized as obstacles.

To challenge the pipe route planning, the study focuses on 2 paradigms in design issue, namely concurrency and interaction, and proposes a design support system for pipe route planning using genetic algorithm (GA)[1][4][5]. As for concurrency, Concurrent Design (CD)[2][8] concerns with more sophisticated designs using considerations of various phases of design simultaneously and cooperatively. The final design must simultaneously meet cost and quality requirements, as well as meet the constraints imposed by activities such as manufacturing, assembly, and maintenance. In the mean time, the radical notion that interactive systems are more powerful problem-solving engines than algorithms is making the new paradigm for computing technology built around the unifying concept of interaction [10]. As for designers who use design support systems as a tool to work on design tasks, thoughts of designers are effectively activated by nice system interactions[6]. The interactions may stimulate the brain of designers to produce some innovative ideas.

As a general approach to piping design, a designer initially creates an appropriate design model, and interactively and iteratively modifies the model in a trial-and-error manner until an appropriate design specification is completed.

The approach in the research focuses on this interactive, iterative and concurrent session of designing. During the designing session using the methodology, various pipe route candidates are generated based on the starting and goal points, and/or several subgoals if necessary, all of which are specified by the designer using a simple operation of pointing device, or mouse, which cannot interrupt the designer's thoughts about piping design. The study uses the GA optimization method in the approach here, however, the goal of the approach is not just to find the best pipe route, but rather to present the designer with several appropriate pipe routes that could assist the designer in finding the best pipe route. A designer could collaboratively develop pipe route planning, referring to the proposed pipe route.

In the following, the basic principle of the method is presented using key ideas which include representation of pipe route for GA operations, spatial potential energy to cover design scenarios, fitness function, basic GA operations, coordinates conversion procedure, and route modification procedure using subgoal setting. In order to apply the method to actual problems and to solve them in a practical manner, the study employs various heuristics, which are concept of direction, generation of initial individuals using intermediate point, extended two-points crossover, and dynamic selection. Those heuristics are also described and their effectiveness in the method is discussed. Then, the paper shows a prototype system, which were developed based on this approach as a GA-based design tool for piping route planning and discusses the validity of the proposed method.

2. Basic mechanism of piping route path generation using GA.

2.1 Genetic representation of piping route path

As an optimal search method for multiple peak functions, GA stemming from the generation of evolution of living things is applied to various optimization problems and its validity has been verified so far [3][7][11] . To apply GA to solve optimization problems in design, design parameters versus character sets of gene, or objective function versus fitness value must be considered and constraint conditions may be included in objective function under a penalty function. In this way, after repeating GA manipulations, a new character set which represents a new generation can reveal the appropriate design parameters.

In order to use GA in piping route path planning as one of the optimization problems, a route path from a starting point to a destination point is represented by a character string and is regarded as a design parameter.

In this approach, a working space for piping route planning is represented by a 2D model and the space is divided into the cells of $M \times N$. A route path is represented using a combination of cells connecting a starting cell and a destination cell. To represent direction of route path, a vector set $\vec{v} = \{\vec{r}, \vec{u}, \vec{l}, \vec{d}, \vec{0}\}$ is defined, each vector represents right, up, left, down and stop, respectively, and character string of 1, 2, 3, 4, 0 corresponds to each vector. Using information on the cells which compose the route path, each individual is coded. For example, the gene type for a route path is expressed using symbols including 1, 2, 3, 4, 0,where zero means the current point already reached the destination cell. Figure 1 shows the vector set and an example of route path C_1 which is represented by $C_1 = \{1, 1, 1, ..., 2, 1, 0, 0, 0, 0\}$.

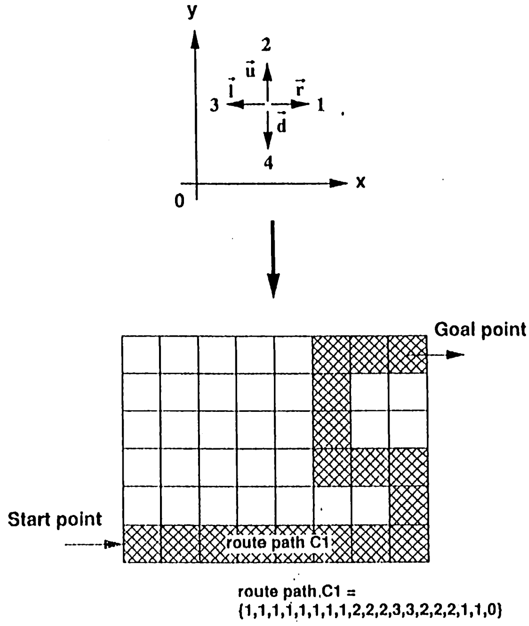

Figure 1. Genetic representation of piping route path

2.2 Spatial potential energy in piping route generation

This section presents a brief overview of the concept of spatial potential energy which we adopted to make favorable route path. In route path planning, high priority is basically given to the shorter route path. In addition to this, various considerations are made; a route must go along the wall and obstacles as much close as possible, avoiding a diagonal path, etc. After these considerations, the most appropriate route path is designed. Using the concept of spatial potential, the degree of access to the wall or the obstacles is quantitatively calculated, and used as a part of objective function for the generation of piping route path using GA.

To determine the distribution of spatial potential, the working space is divided into

$M \times N$ (M=1,2,...; N=1,2,...) unit cells. For example, those cells which contain any portion of the obstacles are given the potential value P_n, and each cell is given the potential value of P_1, P_2,...,P_{n-1} according to the distance from the obstacle cell. Those cells which are located next to the wall are given the potential value P_0, which means that the route path is more favorable if it goes along with the wall. Only the positive values are used as a potential energy. The higher value means that the cell is far from the wall or the obstacles.

2.3 Studies on crossover method

Determination of crossover methods depends upon the application. For example, unicrossover is suitable for the case that each gene has individual information, blend crossover is suitable for the case that genotype has a continuous value. In the case of piping route path, genotype shows a continuous value. A route path must connect a starting and a goal points. In addition to that, considering the layout of equipments, physical conditions for temperature, maintenance and so on, the most appropriate route path among various candidate route paths is designed.

In other words, how to reach the goal point is the important thing to consider. A route path must connect the two points or starting and goal. The length of genotype is variable and not fixed, which means that a genotype is elastic like a rubber band.

Sometimes, genes having different length must be crossed over. To cover the difference in length, we do as follows as shown in Figure 2. Set the length of parent 1 to l_1, and that of parent 2 to l_2 where $l_1 \geq l_2$. Then set the half of l_1 to l_b, multiply l_b with a random number between 0 and 1, and give l_p. The portion between 0 and l_p and the portion between l_b and 1 are exchanged. Since the length of genes may differ each other, additional vector array may be inserted if the length of generated gene is too short to connect each end of the parent gene. To avoid generating genes including obstacles, potential value of each cell is checked to see if the cell in on the obstacle. If it is, a vector is repeatedly generated until it does not on the obstacle. In this way, we could obtain those genes which does not contain obstacle cells in the earlier generations. As a result, a wide range of search area is considered in GA.

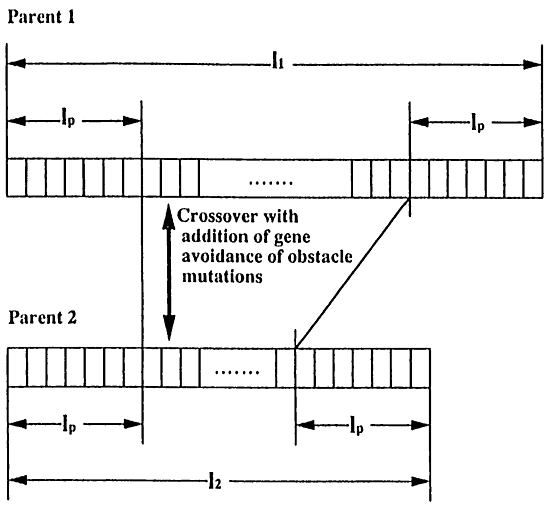

Figure 2. Crossover method for parents with different length

From the results of simulations, two-points crossover tries to avoid obstacles, aggressively find a new route path, and can find a better route path during an earlier generations. On the other hand, uni-crossover can inherit the characteristics from each parents at the same ratio, do not change the genotype, easily to conduct crossover operations even between parents with different lengths, and can generate various kinds of vector arrays. We mainly applied two-points crossover operation but also applied uni-crossover operation as a control.

2.4 Definition of fitness function

In general, piping route path planning is considered from various perspectives. Some of the typical perspectives to the planning would be (a) shorter length of route path, (b) arrangement of the pipes under the same categories, (c) guarantee the maintenance spaces, and so on. Our study considers the shorter length of route path and, from this respect, elements for fitness function were studied. We also considered that the route path should be as straight as possible but no diagonal path is permitted. The number of turning points in the path should be considered. The path should go along the surrounding wall in the work space or obstacles placed in the work space as close as possible. The potential energy is set lower in these cells. Considering these elements, fitness function was defined as shown in (2.1).

$$f(x) = f_0 + f_1 + p_{max} + C + W \quad (2.1)$$

f_0 accumulates the number of cells and gives the length of route path. Length of route path is evaluated in f_0, but it is not enough to cover a variety of route paths. We applied the function f_1, which accumulates the total potential values for the route path and p_{max}, which considers the maximum value of potential energy in the cells of the route path. Every time the direction of route path is changed, a certain weight is added to the fitness value as C in (2.1). If a route path is on any obstacles, or the path contains cells including obstacles, a large weight W is added to the fitness value as shown in (2.2).

$$W = p_{obstacle} \times A \quad (2.2)$$

3. Approach to piping route path planning

The basic mechanism described in the previous section can give an idea to generate appropriate route paths connecting between the starting and goal points. In addition to this, the study uses several heuristics to apply the idea to piping route path planning in order to generate paths more effectively. This sections describes some of the features in these heuristics.

3.1 Introduction of tendencies of directions in chromosome

A gene goes from a starting point towards a goal point. The most important thing is that a gene must reach the goal point for sure, which means that a gene possesses the characteristics that it moves towards the goal. Otherwise, a gene randomly goes inside the search area, which is time consuming and a waste of time.

We define the concept of "zone" to give chromosome the tendencies in the direction of route path from a current position towards the goal point. Using coordinates of current cell and goal cell, a zone is determined in each cell and priority vector is set to each zone. If the priority is set too high, however, all chromosomes have the same tendency in direction and route path cannot be appropriately generated. The appropriate priority was, therefore, set in a trial-and-error manner to generate chromosomes having variety of route paths.

Using the concept of tendencies in direction for route path, we could make route paths under control and give them the tendencies so that the paths are likely to go towards the goal point. Consequently, initial individuals are effectively generated. The method is also applied when an additional portion is patched to cover the shortage of route path in crossover operations.

3.2 Introduction of intermediate point for initial individual generation

Using a starting point and a goal point, initial individuals are randomly generated before GA procedure. First, the zone of a current cell is determined using coordinates of a starting and a goal points. A roulette based on the ratio of priority vector in the zone is set up, an arbitrary point on the roulette is determined using a random number generator between 0 and 1, and the first gene is selected. A current point is forwarded using the selected vector, and the coordinates of the updated current cell are obtained. Then the current zone is set up based on the updated current cell and the goal cell. The same procedure is repeated until the current point reaches the goal cell. In this way, initial individuals are generated.

In the mean time, to find the most appropriate route path, the initial route path should be as random as possible in the working area. Without considering obstacles, route paths are generated only by the specified cells for the starting and destination points. But most of the route paths in the initial individuals may have the tendency to go straight to the goal point. The route paths using these initial individuals did avoid obstacles and reached the goal point in the end. Judging from the route path length, the number of turnover and overall observations, the most appropriate route path is not always found.

To generate initial individuals more randomly, we defined intermediate points to be passed in the route path and applied in our approach. Making a bisector cutting through the line which connects the starting cell and the destination cell, an arbitrary cell on the bisector is selected. Making an arbitrary line passing through the bisector cell from the starting cell to the destination cell, initial individuals are generated referring to this line. Since the arbitrary cell is randomly selected, the route paths cover the overall working space.

3.3 Extended crossover methods

Using the appropriate initial individuals generated in the method mentioned in 3.2, we conducted simulation of piping route path planning using several crossover methods. As results, the followings were observed; (1) Uni-crossover converges individuals at the earlier generations; (2) Uni-crossover does not always exclude those individuals which include obstacle cells; (3) Two-points crossover is superior to uni-crossover.

Although two-points crossover generated appropriate route paths, some of them seem to be a locally optimized route paths. To avoid that, we applied dynamic selection ratio based on the minimum fitness value, average fitness value and the number of cells on obstacles. The first selection ratio of 40% is used until all of the individuals become obstacle free. Then the ratio is set down to 3% and to study all the possible route paths. When the convergence status becomes a certain level, the ratio is set back upto 40%. If the difference between the average fitness value and the minimum fitness value is below 5, we assumed that the convergence is going to terminate. In this way, we excluded those individuals including obstacles in the earlier generations, we tried to take time to find the most appropriate route path without converging to a locally optimized route path. When individuals are likely to converge to an appropriate route path, convergence speed is accelerated. We call this method as "extended crossover method" and applied to our prototype system.

4. Piping route path planning system

We have developed a prototype system for piping route path planning using GA approach. The system is composed of two module layers as shown in Figure 3. The outer layer is

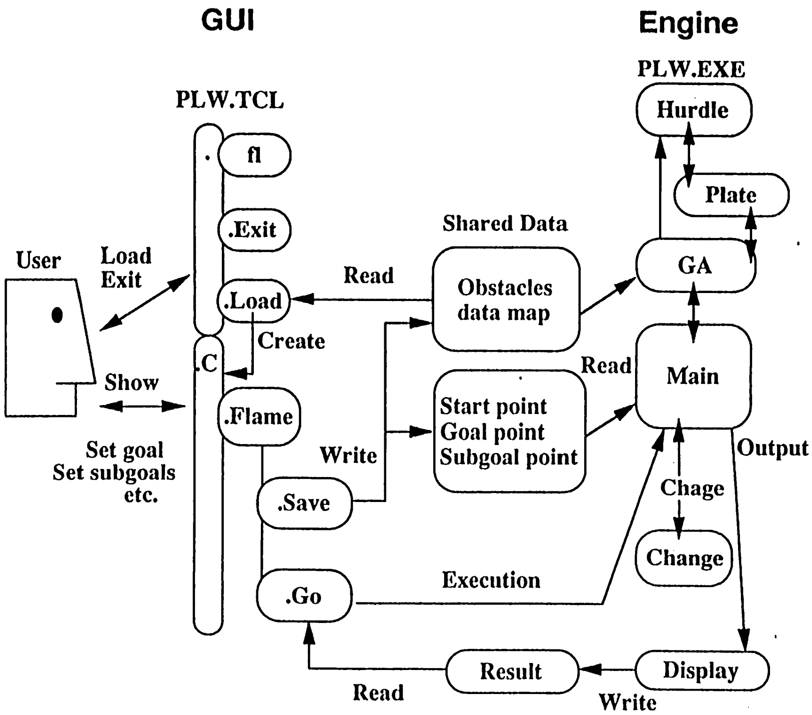

Figure 3. Over view of system architecture

a user interface module with which users directly interact using simple mouse operations and obtain the planning results displayed on the module. The inner layer is a GA engine module, which makes optimization of piping route path based on the parameters given by the users and returns the result back to the interface module.

As for the operation in using the system, a user determines the size of unit cell and divides the working area into $M \times N$ (M = 1, 2,...; N=1,2,...) using the unit cell. Considering the layout of machines or component equipments, the user arranges obstacles with mouse manipulation. Then, the user sets the starting and goal cells, the user may also set subgoal cells if necessary, and stores the parameters. The optimized route paths generated only based on the starting and goal points are not always appropriate in terms of piping route path planning.

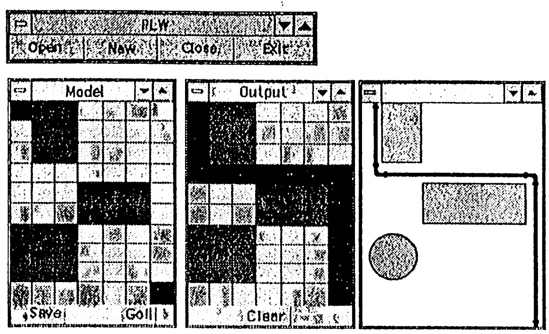

Figure 4. Snapshot of piping route path planning operation

For example, even if a path is not the shortest of all the candidates route paths, it might be an appropriate path because it goes through a certain point. We have realized the setting of subgoal in GA route path planning. The GA engine will calculate route paths based on the given parameters and display proposed paths for the route path planning. Figure 4 shows a snapshot for this operation.

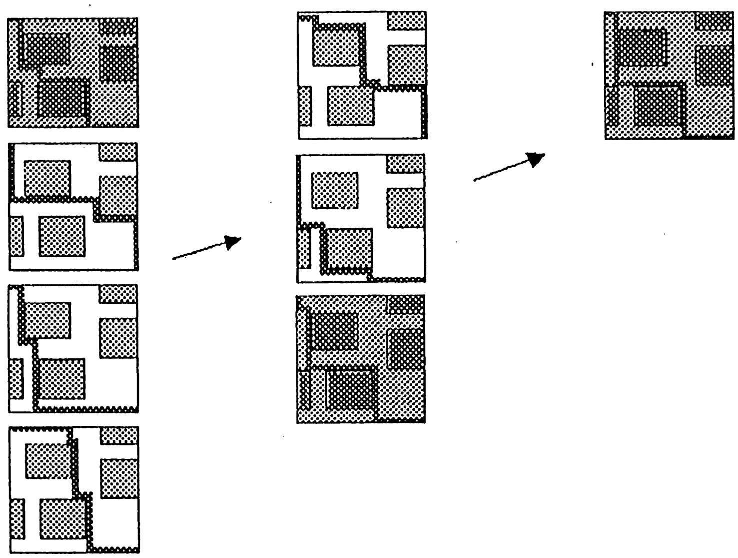

Figure 5. Candidate route paths during convergence with GA operations

The paths proposed by the system include not only the finally optimized route path but also those paths which were generated during GA operations before the convergence of route paths. It is the designer who evaluates those paths and decides to adopt one of these paths, or make another try to consider it from some different perspectives. Figure 5 shows an example of route path planning using the system. Several candidate route paths are displayed during the optimization procedures.

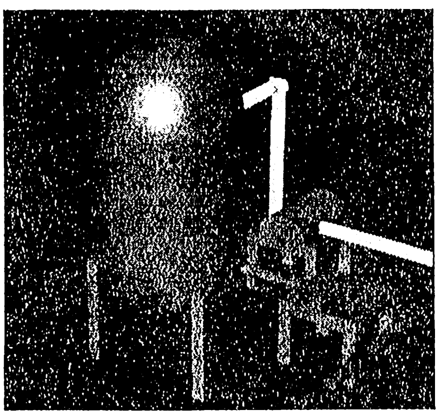

Figure 6 An Example of pipe route planning under integrated environments

Integrating the systems with other design tools such as 3D CAD or a CG tool, route path planning using the system will provide more visualized environments where the users are stimulated their ideas in designing the appropriate route path. Figure 6 shows an example of route path planning using the integrated environmets.

5. Concluding remarks

The paper describes the method used to conduct pipe route planning using GAs. The definition of genes to deal with a piping route path, the concept of spatial potential energy, the method to generate initial individuals, the zone concept in route path generation using GAs, evaluation of crossover methods, definition and application of fitness functions are described. In order to apply the method to actual problems and to solve them in a practical manner, the study employs various heuristics, which are concept of direction, generation of initial individuals using intermediate point, extended two-points crossover, and dynamic selection. Those heuristics are also described and their effectiveness in the method is discussed.

The prototype system, which has been developed to conduct pipe route planning using GAs based on the method, gives designers an environment to design a piping route path in an interactive and collaborative manner with a very simple operation. Although the pipe route planning is limited to two-dimensional spaces in the current version, and the fitness function used in the method is rather simple, the result of simulation shows the validity of the proposed approach towards concurrency and interaction.

The followings will be studied for the future works: higher performance of processes to cope with interactive designing more effectively, consideration of more complicated conditions using various kinds of fitness functions, pipe route planning in three-dimensional spaces, and integration with computer-aided design (CAD) systems.

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(1997年5月8日受付)
(1998年6月10日採録)

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