International Journal of Civil Engineering

Construction Management

Estimation of the speed of soil excavation by fuzzy inference system

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Received: January 2013, Revised: June 2013, Accepted: December 2013

Abstract

Many wide discrepancies have been seen between the determined speed of machinery using handbooks and the actual values in the domestic projects. Hence, uses of modification factors are applied to consider the environmental effects, type of the project and status of site management. But the different statuses of various factors of the domestic projects and international projects should be taken in to account. This paper is aimed to develop a fuzzy system to estimate soil excavation rates at earthmoving jobsites. The proposed fuzzy system is based on IF-THEN rules; a genetic algorithm improves the overall accuracy. The obtained results clearly revealed the capability and applicability of the proposed system to properly estimate soil excavation speed. The average error of fuzzy system handbook method and nearest neighbor interpolation are 10, 92 and 32 percent, respectively.

Keywords: *Machinery Speed, Fuzzy System, Genetic Algorithm.*

1. Introduction

Since civil projects are usually associated with cost consuming excavation operations, developing some approaches to reduce the costs seems necessary. Due to the fact that a high percentage of the project costs are equipment cost, optimal allocation of them may result in notable cost-saving. For this purpose, it is necessary to make an accurate estimation of the required time for each activity ; one of these activities is soil excavation. The required time for soil excavation can be determined using soil volume and soil excavation speed which can be found in manufacturer's handbooks. However, it should be noted that the speed specified by international manufactures cannot be properly utilized in the domestic projects. Accordingly, developing a system to determine the speed in domestic excavation projects is vital. Some researches have been done on different aspects of earthmoving operations [1], [2], [3], but there has not been any research on the mentioned system.

Excavation is a repetetive activity; thus, all related roles to repetetive activities are valid for it. In accordance with literature review, it was realized that there are many studies on different aspects of the repetitive activities in industry and civil.

For example, in industry, Tavakkoli-Moghaddam et al applied a hybrid meta-heuristic algorithm for the vehicle routing problem [4]. Kumar et al used approach for machine loading problem in flexible manufacturing system [5]. In civil projects, Yang et al scheduled repetitive construction projects with uncertain supply of resources and funding [6]. In other researches, authors introduced a genetic algorithm-based method for scheduling repetitive construction projects [7]. A fuzzy repetitive scheduling method was applied by Maravas et al [8]. Hyari et al planned and scheduled Repetitive Construction Projects [9]. Yi et al created and developed network for Repetitive-Unit Projects [10].

In spite of the several existing studies on repetitive activities, a comprehensive study on estimating the speed or associated time to this type of activities is still missing. In other words, in all other studies acitivity durations were known eaither in the form of crisp or fuzzy values. As the result, in this paper, a fuzzy system has been developed for estimating soil excavation speed which has a wide application in the construction projects. Fuzzy systems are popular techniques that have been the focus of significant amount of studies in recent years. For instance, authors presented a fuzzy system to solve the problem in selecting project managers in construction companies [11].

Lin et al [12] utilized fuzzy system for material substitution selection in electric industry. Rau et al [13] used fuzzy technology to develop negotiation framework for automating B2B processes in the RosettaNet environment. Sun et al [14] used fuzzy programming to Optimize material procurement planning problem. Taylan et al [15] developed an adaptive neuro-fuzzy modeling and control systems for Determining optimal quality

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distribution of latex weight.

In this research, in order to construct the primary fuzzy system, fuzzy c-mean clustering method -which is one of the automated data-driven based methods- is utilized [16]. In addition, it was aimed to optimiz fuzzy system parameters ; because once a fuzzy model is developed, in most cases it needs to be optimized. In this paper, during the optimization process the model structure (reasoning parameters) and the membership functions parameters were adjusted.

Among various methods for optimization, evolutionary algorithms (EAs) have been widely used for optimizing fuzzy models because of their ability in searching for optimal solutions in an irregular and high dimensional solution space. For example Aliyari et al in two researches applied the mentioned algorithm for tuning ANFIS parameters [17] [18]. In most applications, the concentration is entirely on the problem, and typically a simple algorithm is used to find a reasonable solution. For example genetic algorithms (GAs) are preferable to traditional search techniques as they do not locate the locally optimal solution. GA has earned great attention in solving engineering problems where large and complicated space exists, and have been used successfully in many applications such as function optimization. For instance, Fdez et al learned the membership function contexts by GA [19].

In this work, GA is used for optimizing the reasoning and membership functions' parameters. The organization of this paper is as follows: First, a brief description of fuzzy system and genetic algorithm is presented. Then, for the sake of developing the fuzzy system, the relevant parameters and their values in different excavation projects are determined. Finally, the proposed system is validated and the obtained results are presented.

2. Fuzzy System and Genetic Algorithm

Recently, different modeling methods based on fuzzy systems and genetic algorithm, have been utilized in many studies for a variety of civil engineering applications. They are complementary tools in building intellectual systems. Such combined systems would be able to estimate the results in other experiments through their generalization ability [20] [21]. This study merges the two potential tools to get advantages from both of them and to eliminate their individual disadvantages.

2.1. Fuzzy system

Fuzzy logic supplies effective solution for nonlinear and relatively unknown processes which is largely because of its ability to blend information from different sources;information such as available mathematical models, experience of operators and process quantifications. It uses linguistic description which facilitates changing the explanation of the system. It is also easy to recall the knowledge and to get in contact with others by using fuzzy natural language for system designers. Moreover, no prior knowledge about the system under control is initially used to formulate the rules and a fuzzy system is constructed from data [22].

Basically, a fuzzy inference system is composed of five functional blocks (Fig. 1):

- A rule base: contains some fuzzy if then rules
- A database: defines the membership functions of the fuzzy sets used in the fuzzy rules
- A decision-making unit: performs the inference operations on the rules
- A fuzzfication interface: transforms the crisp input into degree of match with linguistic values
- A defuzzification interface: transforms the fuzzy result of the inference into a crisp output

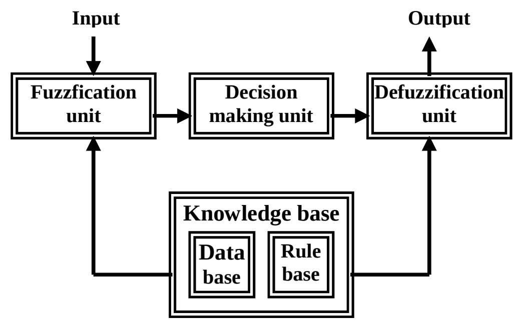

Fig. 1 Basic structure of fuzzy inference system [22]

In fuzzy systems, some fuzzy IF–THEN rules are used to represent the relationships between input and output variables. In each rule, status of each input and output is represented by a fuzzy number. So the number of fuzzy numbers in each fuzzy rule is equal to sum of number of inputs and outputs. Output determination using fuzzy rules contains four steps:(i) to compare the input variables with the membership functions on the premise part to obtain the membership value of each linguistic label, (ii) to combine the membership values on the premise part to get firing strength of each rule, (iii) to generate the qualified consequent (either fuzzy or crisp) of each rule depending on the firing strength, and (iv) to aggregate the qualified consequences to produce a crisp output [23].

There are several types of fuzzy reasoning. In the used type, the overall fuzzy output is derived by aggregating rules' fuzzy outputs. Each fuzzy rule is a function of firing strength and the output membership function of each rule. Various methods have been proposed to determine the final crisp output using overall fuzzy output.

2.2. Genetic algorithm

The genetic algorithm (GA) is a heuristic method that can efficiently optimize functions. At first this algorithm was using binary coding. Recently some researchers have used real coding in genetic algorithm [24] [25]. In the real coding which is used in this research, related operations are performed using the decimal code. This algorithm at first chooses the initial population. The population is large enough to cover the whole solution space. Then three stages (reproduction, crossover and mutation) ,which are the main stages, are iterated until no improvement of the objective function would be obtained.

a. Reproduction

In each reproduction, a new population of individuals is created by selecting from the previous population. Selection is performed on the basis of the roulette-wheel selection [25]. In other words, the higher fitness values the member has, the higher probability of selection for survival and reproduction it will have.

b.Crossover

Crossover operator involves two individuals. For the two individuals, a random integer i with components between 0 and the dimension of the individual is drawn. All the components situated on the left or right (it is determined at random) of this crossing point are not affected and those situated beyond the crossing point are exchanged. The new coordinated values of the components a(i) and b(i) of two individuals a, and b are calculated as follows:

$$a'(i) = a(i) + \Delta b - \Delta a$$
$$b'(i) = b(i) + \Delta a - \Delta b \quad (1)$$

Δa And Δb are calculated as follows:

$$\Delta a = \frac{a(i)}{M}, \Delta b = \frac{b(i)}{M} \quad (2)$$

M is a random number between 0 and 1000.

c. Mutation

The mutation operator involves one individual. For the individual, a random integer i between 0 and the dimension of the individual is drawn. The new $a'(i)$ is calculated as follows:

$$a'(i) = a(i) \pm k * \Delta a \quad (3)$$

$$\Delta a = \frac{Up(i) - Low(i)}{M} \quad (4)$$

Where M is a random integer number between 0 and 10, Up(i) and Low(i) represent the superior extent and the inferior extent of a(i) component of individual a to be disturbed.respectively, k is a coefficient at first equal to 1 and reduced gradually, and the sign is selected at random [24].

3. Parameters of Soil Excavation

In order to develop the fuzzy system of estimating the soil excavation speed, variable parameters and their changing range should be determined. For this purpose, some studies have been performed and a system was prepared to measure and record the speed and other relevant data from past projects. The obtained results are summarized as follows:

- Equipment life time (normally a value between 2000 to 100000)
- Status of equipment maintenance (good, fair, relatively poor and poor)
- Technical skill of the operator (good, fair, relatively poor and poor)
- Number of successive excavation days (a value between 3 and 7).
- Soil type (sand, sandy clay, clay, gravel and crushed rocks).
- Presence of rocks in soil (yes, no).
- Ground slope (a value between -20 and +20 degree).
- Operation time (Morning, Afternoon, Night).

Average temperature during operation (a value between -15 to 45).

4. Fuzzy System of Estimating Excavation Speed

4.1.-Collection of past data collection

The first step to develop a fuzzy system is to collect historical data. In this study, 113 data was used, 100 of which were utilized for training and the remaining were used for system validation.

4.2. System structure determination

The fuzzy system structure can be determined through obtaining fuzzy rules and appropriate membership functions for inputs and outputs.

4.2.1. Fuzzy rules generation

To generate fuzzy rules, the inputs and outputs data should be clustered. The clustering should be performed in a way that similar data are placed in the same cluster and the data of different clusters are as dissimilar as possible. The above mentioned approach is applicable to the crisp clustering and in the fuzzy clustering; each data belongs to all clusters and have a distinct membership value to each cluster. These indicate the strength of the association between that data element and clusters.

To create fuzzy rules, first only the output space is clustered. Then, the input clusters are determined through projection of each output cluster to each input space. Projection means to assign membership value to the input data equal to the output data.

In order to cluster the outputs, the fuzzy c-mean clustering method was used. In this method, first, initial centers of clusters are determined randomly. Then, the membership value of each data to each cluster is determined by calculating distance between data and cluster center. Afterward, center of clusters are again determined using data and membership value of data. This process continues until the distance between each of the clusters in the two successive processes will be lower than a specified value. The number of iteration relies on the required accuracy [16]. Equations (5) and (6) represent the relevant equations:

$$u_{ik} = \left(\sum_{j=1}^{c} \left(\frac{D_{ik}}{D_{jk}}\right)^{\frac{2}{m-1}} \right)^{-1}, 1 \le i \le c \tag{5}$$

$$v_i = \frac{\sum_{k=1}^{n} (u_{ik})^m x_k}{\sum_{k=1}^{n} (u_{ik})^m}, 1 \le i \le c \tag{6}$$

Where u_{ik} is degree of membership of data k in cluster i, D_{ik} is distance between data k and cluster i, v_i is center of cluster i, n is number of data, c is number of clusters, x_k is data k and m is system fuzzy coefficient (a value between 1.5 and 2.5 and is usually considered 2)

The above-mentioned clustering should be performed for different numbers of clusters. Several criteria have been proposed for the appropriate number of clusters. In this research, the criterion proposed by Lee [26] has been followed. The big size of this criterion shows its appropriateness [26]. Equation (7) presents the mentioned criterion.

$$COC(c) = \frac{\frac{1}{n} \sum_{k=1}^{n} \max_{1 \le i \le c} \{u_{ik}\} - \frac{1}{c}}{1 - \frac{1}{c}} \tag{7}$$

Through using fuzzy c-mean clustering algorithm, the best number of clusters and coc index were determined equal to 6 and 0.8244, respectively. The Fig. 2 shows the output clusters.

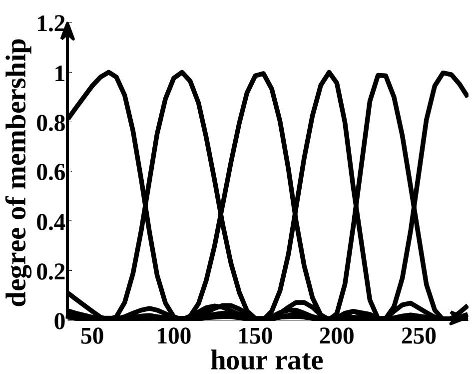

Fig. 2 Output clusters

On the basis of mentioned clustering approach, for multi-option variables, such as using (or not) ripper, each option will have several (instead of one) membership values in regards to each cluster. Membership value of each option to each cluster was calculated by averaging between some membership values. It is illustrated in the following Fig. 3.

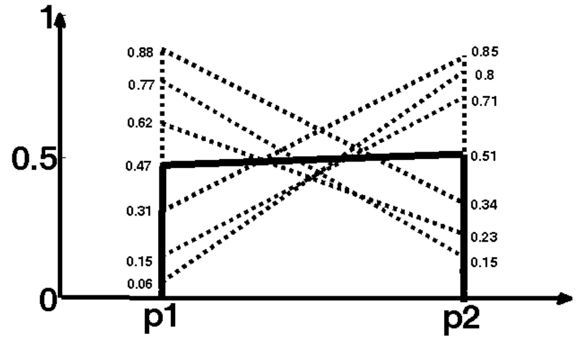

Fig. 3 Determining membership value of two-option variable

4.2.2. Membership function generation

After clustering the output data, clusters created on each output should be projected on the input space so as to determine input clusters. Then, appropriate membership functions were established for each output and input cluster. Gaussian membership functions were used for all input and output variables (except the multi-option variables) because they can approximate almost all types of membership functions by changing the parameters shown in equation (8) [27].

$$\mu = \exp\left(-\frac{(x-c)^2}{2\sigma^2}\right) \tag{8}$$

Where, μ is membership value, c is centre of membership function and σ is width of membership function (standard deviation). The following figure depicts Gaussian membership function and its parameters.

Initial parameters of membership functions are determined so that the difference between the membership value of each data to each cluster and the membership value of each data to the resultant membership function, become minimum.

Membership function shape of 2, 3, 4 and 5 option variables (based on mentioned issue in section 4.2.1) are 4, 5, 6 and 7 sided shape, respectively. Fig. 5 presents the membership functions and their parameters.

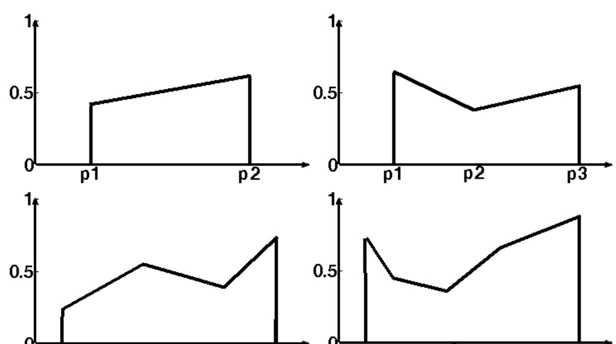

Fig. 5 4,5,6 and 7 sided shapes for 2,3,4 and 5 option variable

4.3. Determining parameters

Parameters determination includes two steps of system inference; parameters determination and best parameters determination for fuzzy input and output numbers. The data has been used for these steps.

4.3.1. Inference parameters determination

As mentioned before, the system output is determined through the five mentioned steps. The output of step 1 can be determined using the values of all inputs and input membership functions in different fuzzy rules. Several operators have been defined for the calculations of step 2 to 4. In general, these operators can be divided into two main categories. The first ones which have similar performance with intersection operators are represented by "T". In other words, T (a, b) is intersection of a and b. On the other hand, the second ones have a similar performance with union operators and are shown by "S". It means that S (a, b) is union of a and b.

T and S operators can be used for more than two numbers. For this purpose, the operator should be applied to the two first numbers and the result is saved. Then operators are used for result and third number. This procedure will be continued until the last number.

There are different definitions for T and S operators. In this research, the relation suggested by Skalar and Schweitzer for t-norm and s-norm was used [28].

$$T(a,b) = 1-[(1-a)^p + (1-b)^p - (1-a)^p(1-b)^p]^{\frac{1}{p}} \tag{9}$$

$$S(a,b) = [a^p + b^p - a^p b^p]^{\frac{1}{p}} \tag{10}$$

The value of "p" is different for different systems and it should be determined based on the available data on the considered field. In this research, the proposed genetic algorithm was utilized to determine the value of "p".

There are two methods for using T and S operators in the steps 2 to 4, namely Mamdani's approximation approach and the formal logical reasoning approach. Contrary to the second method, the first method uses T operator for step 2, 3 and S operator for step 4. In this study, linear combination of these two methods has been utilized and relevant factor "w" to the linear combination was computed.

After determining the fuzzy output, the crisp output should be determined. To achieve that, the proposed relation by Filev and Yager was used [29].

$$\bar{y} = \frac{\int (\mu)^\alpha y dy}{(\mu)^\alpha dy} \qquad \alpha > 0 \tag{11}$$

Where, μ is membership value and α is a coefficient which as well as above-mentioned parameters should be determined.

Genetic algorithm was utilized to determine the parameters. The objective function was system error described as follows:

$$PI = \sum_{i=1}^{N} \frac{(y^i - \hat{y}^i)^2}{N} \tag{12}$$

Where, PI is system error, y^i is desired output, $\hat{y}^i$ is system output and N is number of data. Due to the high volume of computations, MATLAB Software was used. The obtained results indicated that the values p, w, and α were equal to 2.35, 0.74, and 2.31, respectively.

4.3.2. Membership functions parameters determination

After inference parameters determination, the parameters related to membership functions which have been specified inaccurately using the fuzzy clustering, should be tuned. Contrary to current methods which membership function parameters are determined separately, all parameters can be tuned simultaneously through using the proposed method. In other words, in Gaussian membership functions, exactly two parameters(c,d) and in 4,5,6 and 7 sided membership functions, exactly 2,3,4 and 5 parameters(p1,p2,p3,p4 and p5) are determined simultaneity. To do this, genetic algorithm has been employed and the objective function was system error.

4.4. System validation

The excavation speed for 13 validation data was determined using the proposed values by the handbook and modification factors. Moreover, the excavation speed was determined by the presented system through considering input values. In addition, the nearest neighbor interpolation was applied to compute the output value. Results of implementing the fuzzy system are compared to three type of output data:

- Results of actual observation (which could be considered as the benchmark for comparison)
- Results of nearest neighbor interpolations.
- Results of using manufacturers' handbooks which is the common practice for estimating rates of excavation in real construction job sites.

Table 1 provides a comparison between the results of fuzzy system, handbook method and nearest neighbor interpolation for the validation data. According to the above table, the average error of fuzzy system, handbook method and nearest neighbor interpolation is 10, 92 and 32 percent, respectively. In effect, this shows a notable decrease in the error estimation of excavation speed.

Table 1 Comparison of fuzzy system output and handbook method

Row	Output data (m^3/hr)	System output (m^3/hr)	System error percentage	Blade factor	Work factor	Ground slope factor	Gear factor	Handbook result (m3/hr)	Error percentage of handbook method	Nearest neighbor interpolation result (m3/hr)	Error percentage of Nearest neighbor interpolation
1	260	221	15	0.9	0.83	1.15	1	515.4	98	194	25
2	80	101	26	0.4	0.76	1.2	0.9	275.8	245	112	40
3	180	193	7	0.8	0.8	1.08	1	400.9	123	151	16
4	140	127	9	0.8	0.7	1	0.85	185.6	33	94	33
5	120	114	5	0.8	0.75	0.93	0.9	190.8	59	148	23
6	55	51	7	0.4	0.77	1.15	1	92.1	67	78	42
7	40	38	5	0.4	0.72	0.73	0.9	107.9	170	76	90
8	95	91	4	0.8	0.75	0.92	0.9	188.8	99	73	23
9	90	80	11	0.7	0.75	1.2	1	119.7	33	66	27
10	60	68	13	0.5	0.75	1.15	1	112.1	87	42	30
11	110	92	16	0.8	0.76	1	0.9	257.2	134	138	25
12	140	129	8	0.9	0.72	0.73	0.9	161.8	16	171	22
13	130	134	3	0.65	0.78	1.15	1	174.9	35	102	22

5. Conclusion

In this paper, the problem of excavation operation as a repetitive activity and the possibility of utilizing fuzzy logic to improve estimation of its speed have been investigated. Fuzzy system, its structure and methodology indicated the efficiency and applicability of the fuzzy system. This favorable accuracy, results from the high capability of the system in the training through using inaccurate data and utilizing effective techniques to improve the system. It should be noted that the reason of inaccuracy of data can be assigned to the inaccuracy of collected data and utilizing the qualitative parameters such as maintenance status. Moreover, in comparison with other studies, the number of used data is lower. This is promising, because if higher number of data is applied, superior results can be obtained.

In the event of using an expert's point of views in the determination of effective parameters and collecting relevant data, the system capability will be increased. This is because all parameters in the excavation operation and their effects are clear and the objective is to develop a system with the minimum number of input to estimate speed through considering effective parameters. Therefore, experts can be used to determine more important parameters. Besides, experts are also useful in determining the most appropriate options for qualitative parameters in different situations.

The importance of the precise estimation of the excavation speed stresses the need for the fuzzy logic utilization in other projects and also more development of the approach. Since systems developed for the estimation should be simple and understandable, it can be expected that this will be considered in the further research. Thus, after preparing the system, it should be simplified from the aspect of fuzzy rules, number of inputs and defined membership functions for each of the variables.

On the other hand, the presented system does have some inherent weaknesses, which can serve as the foci of future research:

- ✓ The data used to create and analyze the system were obtained through projects that were performed in a particular country, Iran. Obviously, the conditions in different countries will vary. This issue must be addressed when using such models.

One important matter to consider when preparing any calculative model is system simplicity. The system presented in this study, in spite of its high affinity for predicting the output, is somewhat complicated. Thus, the system should be simplified in terms of input number (i.e., parameters of soil excavation) or the previously acquired data used.

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