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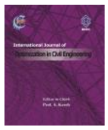

OPTIMUM SELECTION OF NUMBER AND LOCATION OF GEOTECHNICAL BOREHOLES BASED ON SOIL RESISTANCE

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ABSTRACT

Digging of geotechnical boreholes and soil resistance tests are time-consuming and expensive activities. Therefore selection of optimum number and suitable location of boreholes can reduce cost of their drilling and soil resistance tests. In this research, a model which is consisting of geo statistics model as an estimator and an optimized model is selected. The kriging calculates the variance of the estimation error of different combinations from available geotechnical boreholes. In each combination, n is number of considered boreholes and N is number of available boreholes (N>n). At the end, the best combination is selected by genetic algorithm (the error variance of this combination is minimum). Also the Kean Shahr of Ahvaz city (in Khuzestan province, Iran) is selected as case study in this research. Location of selected boreholes is in points that soil resistance of these points represents mean soil resistance of total region. Optimum number of boreholes is 15. Also results show that location of selected boreholes depends to soil resistance and diameter and length of applied piles are not important for this purpose.

Keywords: soil resistance; kriging; genetic algorithm; the Kean Shahr; geotechnical boreholes.

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1. INTRODUCTION

For construction of the apartments, bridges, different industrial factories and etc, digging geotechnical boreholes and testing of soil resistance is necessary. These activities are time-consuming and costly. Therefore selection the optimum number and suitable location of geotechnical boreholes is an important issue for geotechnical studies.

In recent years, researchers considered economic and technical problems for digging

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boreholes. Some of them applied optimization methods for this purpose.

Fenton [1] studied about applied tools in stochastic soil models as the sample covariance, spectral density, variance function, variogram, and wavelet variance functions. He compared abilities of finite scale models and fractal models for estimation of soil characteristics. Goovaerts [2] used two dimensional kriging for estimation of heavy metal concentrations. He showed that kriging is a suitable method for estimation of variables with positively skewed histograms. Yupeng & Miguel [3] developed a new method for estimating experimental variograms. This method can utilize available data-set is typically sampled over a sparse pattern at irregularly spaced locations while conventional method can only use from a regular pattern for calculation of variograms. Asa & et al. [4] applied three linear kriging (simple kriging, ordinary kriging, and universal kriging) and three nonlinear kriging (indicator kriging, probability kriging, and disjunctive kriging) algorithms. Their vatiogram was spherical and data format was vector and raster. They compared results of different kriging algorithms. They observed that probability kriging with the vector data has the best results for interpolation of soil data in transportation projects. Bowman & Crujeiras [5] applied different variograms for simulation pollution data in Galicia (north-west Spain).

In recent years Adib & Moslemzadeh [6], Razafimahefa & Anctil [7] applied different kriging methods for determination of location of rainfall gauging stations. Also Oliver & Webster [8], Mehdad & Kleijnen [9] and Firouzianbandpey & et al. [10] applied different kriging methods and variograms. Wu and et al. [11] applied GA method and kriging simulator model for optimization of pollution monitoring network. They minimize error variance. Jimenez & et al. [12] optimized a monitoring network for lakes and reservoir dams by GA method. They determined location of new stations that must be added to network. Ruiz-C´ardenas & et al. [13] applied Hybrid Genetic Algorithm (HGA), GA method and SA method for optimization of monitoring network. HGA is combination of GA method and stochastic search algorithms. Also in recent years Ahmadianfar & et al. [14, 15] and Adib & Samandizadeh [16] applied GA methods for optimization of volume of released water from dam reservoir.

The purpose of this research is selection geotechnical boreholes from entire of available geotechnical boreholes so that they can determinate best estimation of soil resistance. Because of digging geotechnical boreholes and testing soil resistance are time-consuming and costly a number of geotechnical boreholes may be eliminated. For determination of optimum combination, authors of this research apply kriging estimator model and genetic algorithm and create a mixed optimization model.

2. THE RESEARCH METHODOLOGY

Variogram function divides to two parts (time invariant and space invariant). Therefore variogram function $\gamma(t_j, h)$ converts to:

$$\gamma(t_j, h) = \alpha(t_j) g(h, \beta) \quad (1)$$

where:

$\alpha(t_j)$: Time scaling parameter (time dependent and space invariant)

β : Shape parameter (time invariant and space dependent)

$g(h,\beta)$: Scaled climatologically varigrom (time invariant and space dependent)

$g(h,\beta)$ can be exponential variogram, spherical variogram, Gaussian variogram or etc. Error variance is:

$$\sigma_E^2(t_j) = \alpha(t_j)\delta_E^2 \tag{2}$$

where:

δ_E^2: Scaled estimation variance

The estimation variance can be expressed (Journel and Huijbergts 1978):

$$\delta_E^2 = \mu + \sum_{i=1}^{N} \lambda_i \bar{g}(h_{iA}) - \bar{g}(h_{AA}) \tag{3}$$

where:

μ : Lagrange parameter

λ_i : Weighted coefficient of station i

$\bar{g}(h_{iA})$: The average of variogram function that is dependent to distance between station *i* and other stations

$\bar{g}(h_{AA})$: The average of variogram when both extremes of the vector *h* describe independently the area *A*.

The scaled estimation variance depends on three factors: scaled climatologically variogram, the number of stations and their locations. This parameter is adopted for variance reduction technique in this paper.

Different combinations of stations produce different error variances. The best combination has the least error variance. Kriging method only determines error variance for each combination. For finding the best combination, an optimization model must be applied. The number of combinations (subsets) with n members is:

$$\binom{N}{n} = \frac{N!}{n!(N-n)!} \tag{4}$$

where:

N is the number of entire of members (available stations) [6].

Link between kriging and GA methods is shown in Fig. 1.

The Kean Shahr is a neighborhood in Ahvaz (31°22'4"N, 48°38'22"E). The Kean Shahr is in northwest of Ahvaz. 30 geotechnical boreholes were dug in this region. Location of these boreholes is shown in Fig. 2.

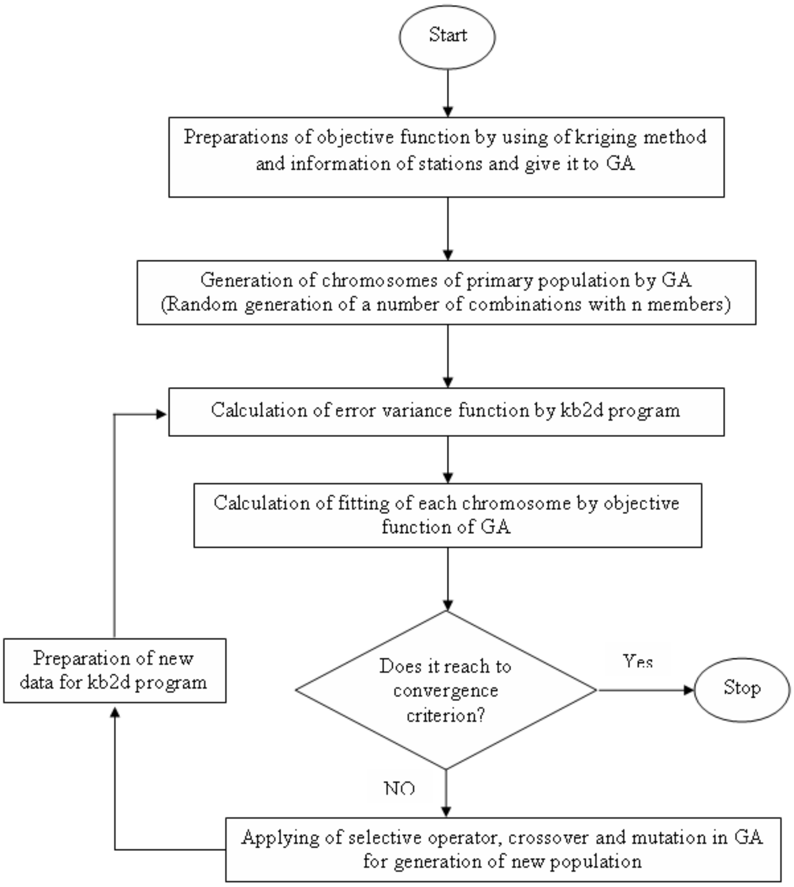


Figure 1. Link between kriging and GA methods [6]

Figure 2. Location of geotechnical boreholes in the Kean Shahr

3. RESULTS AND DISCUSSION

In this research, different variograms were tested and variogram that has the least variance was selected. This variogram is a spherical variogram. Its nugget effect, sill, range, minor range and major range are 0.1439, 0.288, 610.4, 375 and 1089 respectively. Also number of blocks in block estimation of kriging method is 8*8 blocks. Using of collected information in 30 geotechnical boreholes, a soil resistance map was prepared. This map is illustrated in Fig. 3.

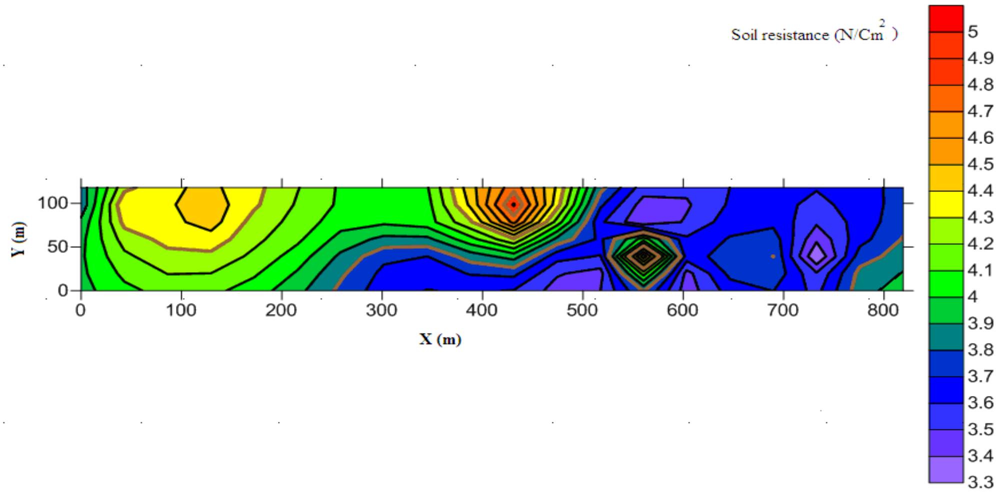


Figure 3. Soil resistance map in the Kean Shahr

After using of kriging estimator model for several states from each combination , these results introduce to GA optimized model and GA determines optimum state for each combination.

Error variances of kriging estimator model and GA optimized model for different combinations (from one geotechnical borehole to 15 geotechnical boreholes) are shown in Table 1 and Fig. 4.

Table 1: The values of error variance of kriging estimator model and GA optimized model for different combinations of geotechnical boreholes

Number of geotechnical boreholes	1	2	3	4	5
error variance	0.3493	0.338	0.3078	0.2757	0.2581
Number of geotechnical boreholes	6	7	8	9	10
error variance	0.2471	0.2355	0.2291	0.2257	0.2234
Number of geotechnical boreholes	11	12	13	14	15
error variance	0.2223	0.2214	0.2209	0.2204	0.2202

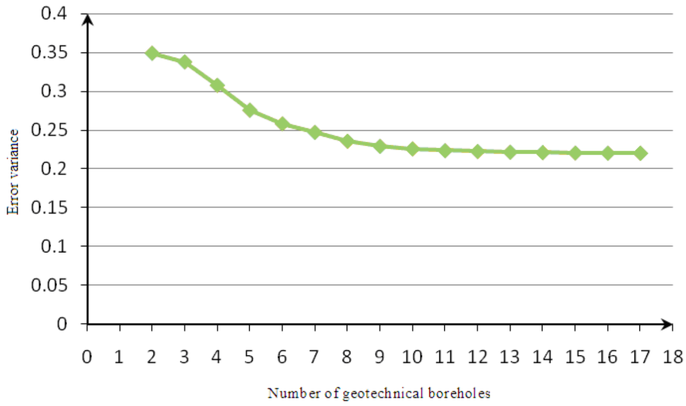
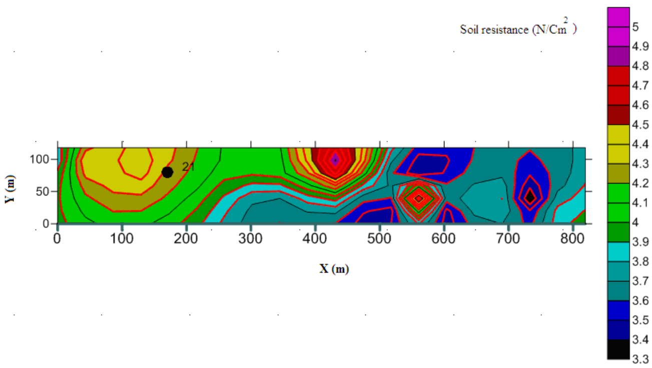
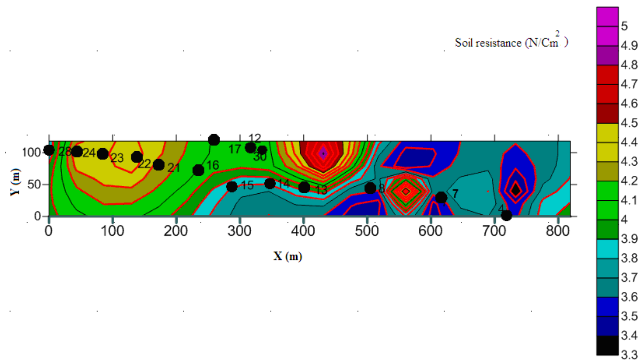


Figure 4. Variations of error variance vs. number of geotechnical boreholes (for optimum spatial combinations)

For example, optimum spatial combination of geotechnical boreholes (optimized by GA method) is illustrated in Fig. 5 for one geotechnical boreholes and fifteen geotechnical boreholes.



(a)



(b)

Figure 5. (a) Optimum combination for one geotechnical borehole (b) Optimum combination for fifteen geotechnical boreholes

Characteristics of GA optimized model are:

Population size: 32 (for determination of optimum combination one to five geotechnical boreholes) -60 (for determination of optimum combination 14 to 15 geotechnical boreholes)

Crossover Probability: 0.5

Mutation Probability: 0.05

The number of generations: 100 (for determination of optimum combination one to three geotechnical boreholes) – 1000 (for determination of optimum combination 14 to 15 geotechnical boreholes)

For finding of optimum combination of four geotechnical boreholes, convergence trend of GA is illustrated in Fig. 6.

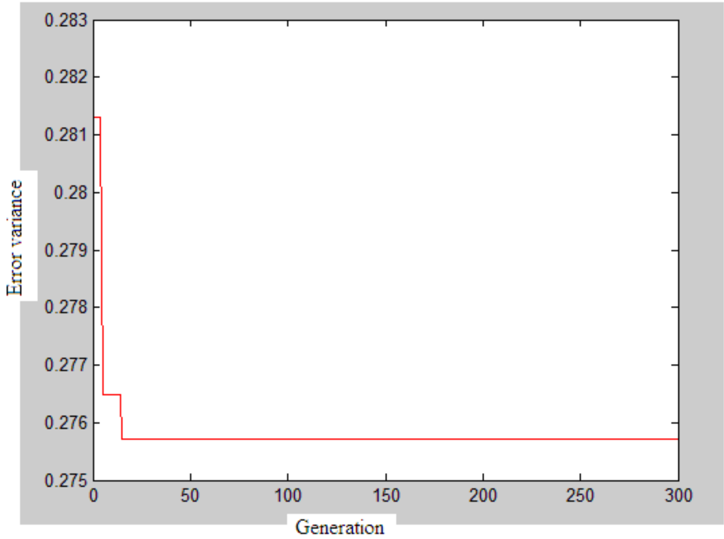


Figure 6. Convergence trend of GA for finding of optimum combination of four geotechnical boreholes

For verification of results of GA, error variance of different selections of one geotechnical borehole as calculated by analytical method. Results of this method was similar to results of GA. Two methods selected geotechnical borehole (no 21) and error variance of their optimal selection is 0.3493.

4. CONCLUSION

In this research a new method was developed for determination of optimum number and location of geotechnical boreholes. If number of geotechnical boreholes is less than optimum number, error variance will increase and measured soil resistance cannot be utilized for the whole region. If number of geotechnical boreholes is more than optimum number, error variance will not decrease and cost of digging of geotechnical boreholes and soil resistance tests will increase. This increases the cost is not necessary and cannot increase accuracy. For considered region (the Kean Shahr), optimum number of geotechnical boreholes is 12 while actual number is 30. Also Fig.5 shows that optimum location of geotechnical boreholes is function of average soil resistance. For example for one geotechnical borehole, selected geotechnical borehole (no 21) locates in point that represents the weighted average of soil resistance. In other words, optimum location of geotechnical boreholes is not in center of region.

Developed methods (using of kriging estimator model and GA optimized model) is a suitable tool for determination of optimum number and location of geotechnical boreholes. This combined method can reduce cost and time of digging of geotechnical boreholes and soil resistance tests and increase accuracy of collected data from geotechnical boreholes.

REFERENCES

1. Fenton GA. Estimation for stochastic soil models, *J Geotech Geoenviron Eng, ASCE* 1999; **125**(6): 470-85.
2. Goovaerts P. AUTO-IK: A 2D indicator kriging program for the automated non-parametric modeling of local uncertainty in earth sciences, *Comput Geosci* 2009; **35**(6): 1255-70.
3. Yupeng L, Miguel C. A flexible lag definition for experimental variogram calculation, *Mining Sci Technol (China)* 2011; **21**(2): 207-11.
4. Asa E, Saafi M, Membah J, Billa A. Comparison of linear and nonlinear kriging methods for characterization and interpolation of soil data, *J Comput Civil Eng, ASCE* 2012; **26**(1): 11-18.
5. Bowman AW, Crujeiras RM. Inference for variograms, *Comput Statist Data Anal* 2013; **66**(Issue C): 19-31.
6. Adib A, Moslemzadeh M. Optimal selection of number of rainfall gauging stations by kriging and genetic algorithm methods, *Int J Optim Civil Eng* 2016; **6**(4): 581-94.
7. Razafimahefa H, Anctil F. Performance and reliability of probabilistic scenarios of interpolated rainfall based on geostatistics, *J Hydrolo Eng*, *ASCE* 2014; **19**(6): 1214-23.
8. Oliver MA, Webster R. A tutorial guide to geostatistics: Computing and modelling variograms and kriging, *Catena* 2014; **113**: 56-69.
9. Mehdad E, Kleijnen JP. Classic Kriging versus Kriging with bootstrapping or conditional simulation: classic Kriging's robust confidence intervals and optimization, *J Operat Res Society* 2015; **66**(11): 1804-14.
10. Firouzianbandpey S, Ibsen LB, Griffiths DV, Vahdatirad MJ, Andersen LV, Sørensen JD. Effect of spatial correlation length on the interpretation of normalized CPT data using a kriging approach, *J Geotech Geoenviron Eng*, *ASCE* 2015; **141**(12): 04015052-1-9.
11. Wu J, Zheng C, Chien CC. Cost-effective sampling network design for contaminant plume monitoring under general hydrogeological conditions, *J Contaminant Hydrolo* 2005; **77**(1-2): 41-65.
12. Jimenez N, Mauricio Toro F, Ve´lez JI, Aguirre N. A methodology for the design of quasi-optimal monitoring networks for lakes and reservoirs, *J Hydroinform* 2005; **7**(2): 105-16.

13. Ruiz-C´ardenas R, Ferreira MAR, Schmidt AM. Stochastic search algorithms for optimal design of monitoring networks, *Environ* 2010; **21**(1): 102-12.
14. Ahmadianfar I, Adib A, Taghian M. A multi-objective evolutionary algorithm using decomposition (MOEA/D) and its application in multipurpose multi-reservoir operations, *Int J Optim Civil Eng* 2015; **5**(2): 167-87.
15. Ahmadianfar I, Adib A, Taghian M. Determination of optimal hedging rule using fuzzy set theory for multi-reservoir operation, *Int J Optim Civil Eng* 2016; **6**(1): 27-42.
16. Adib A, Samandizadeh MA. Comparison ability of GA and DP methods for optimization of released water from reservoir dam based on produced different scenarios by Markov chain method, *Int J Optim Civil Eng* 2016; **6**(1): 43-62.