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GLOBAL OPTIMIZATION OF GRILLAGES USING SIMULATED ANNEALING AND HIGH PERFORMANCE COMPUTING

Dmitrij Šešok[1], Jonas Mockus[2], Rimantas Belevičius[3], Arnas Kačeniauskas[4]

[1, 2]*Systems Analysis Department, Institute of Mathematics and Informatics, Akademijos g. 4, LT-08663 Vilnius, Lithuania*

[1, 3]*Department of Engineering Mechanics, Vilnius Gediminas Technical University, Saulėtekio al. 11, LT-10223 Vilnius, Lithuania*

[4]*Laboratory of Parallel Computing, Vilnius Gediminas Technical University, Saulėtekio al. 11, LT-10223 Vilnius, Lithuania*

E-mails: [1]dsesok@gmail.com; [2]jmockus@gmail.com; [3]rb@vgtu.lt; [4]arnka@vgtu.lt

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Abstract. The aim is to investigate ways of increasing the efficiency of grillage optimization. Following this general aim, two well-known optimization methods, namely the Genetic Algorithm (GA) and Simulated Annealing (SA), were compared using some standard medium size (10 and 15 piles) examples. The objective function was the maximal vertical reactive force at a support. Coordinates of piles were optimization variables. SA wins and was applied to real-life problem (55 piles) by parallel computations performed using a powerful cluster. New element is comparison of SA with GA and application of SA to a practical problem of grillage optimization.

Keywords: Grillages, Simulated annealing, Global optimization, Finite elements, Genetic algorithms.

1. Introduction

Grillages are one of the common types of civil engineering structures that are widely used, e.g. in construction of so-called grillage-type foundations. This is the popular and effective scheme of foundations, especially in case of weak grounds. In this paper we shall concentrate on optimization of this particular type of foundations, which will be called simply "grillages".

Grillages consist of supporting piles and connecting beams resting on them. Piles are the terminal element of the erection, which distribute the loadings coming from the erection through the connecting beams. Usually the reinforced concrete piles are manufactured at the factory, and their dimensions are determined during the design stage. Having this in mind, the optimal grillage should meet twofold criteria: the number of piles should be minimal, and the connecting beams should receive minimal possible torques what results in minimal consumption of concrete for beams. In fact, here we encounter two separate optimization problems: search for minimal number of piles and search for minimal volume of beams. Both problems can be integrated into one with a compromise objective function. In this paper we assume that the characteristics of piles and beams are known and consider the first optimization problem.

Initial data for the grillage optimization problem are the following:

- The geometrical scheme of connecting beams.
- Cross-section and material data of all beams (area, moments of inertia, elastic constants).
- Positions of immovable piles (if any).
- Maximum allowable reactive force at pile.
- Minimum possible distance between adjacent piles.
- Stiffness of pile.
- Loading data. Active forces can be applied in the form of concentrated loads and moments at any point on beam, or in the form of distributed trapezoidal loadings at any segment of beam.
- Number of piles (obtainable dividing the total loading by a carrying capacity of pile).

Results of optimization are such positions of all piles for which the reactive forces do not exceed the carrying capacities at any pile. If such a placement is not possible the number of piles should be increased. In an ideal grillage reactive forces at all piles are identical. This makes the problems attractive from the mathematical point of view since it can be estimated how far the best value found is from the ideal one.

Previous works. Whereas the beam optimization problems in form of optimal sizing of beams in grillage structures under given boundary and loading conditions (see, e.g. (Chamoret *et al.* 2008) and references therein) or optimal layout of grillages (e.g. (Rozvany 1997)) attracted lot of attention, only a few papers deal with the optimization of pile placements schemes. In (Kim *et al.* 2005) an optimal pile placement scheme under the raft is

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sought that minimizes the differential settlements of the raft using genetic algorithms. The local search algorithms were employed for optimal placing of piles under a separate beam of grillage (Belevičius and Valentinavičius 2001) and under whole grillage using iterative algorithm on the basis of mentioned work (Belevičius *et al.* 2002). Experience shows that the objective function for practical grillage optimization problems possesses many local minima points. Due to this the local search obviously is not proper choice, and global optimization algorithms are the necessity. The deterministic global optimization algorithms proved to require non-realistic computer resources for even small-scale grillage optimization problems (Čiegis *et al.* 2006). Promising results for larger-scale grillages (up to tens of design variables) were achieved with Genetic Algorithms (GA) (Belevičius and Šešok 2008). The potential of Simulated Annealing (SA) for sizing optimization of grillage beams is illustrated in (Kripka 2005), but only for small problems, up to 10 design variables.

Experimental calculations of this paper show that SA is more efficient as compared with GA. This is the first new element. Another new element is investigation of practical limits of SA by solving the pile placement optimization problems up to 55 design variables using implementation of SA algorithm for parallel computations on a cluster of 40 homogeneous computers.

2. Grillage optimization model

The objective function is defined by finite element method. The girders of grillage are approximated as beam elements with fixed cross-section and material characteristics. The piles are represented as the supports with specified displacements (zero displacements are the most common case). Alternatively, piles are regarded as supports with specified stiffness characteristics. Supports of the first type are rather non-realistic representations and sometimes yield misleading analysis results. For example, when multiple supports are needed to carry large concentrated load, this kind of supports will lead to a logjam. If odd number of supports is placed under load, the central support will be located just beneath the load and will take all the force. In case of even number of supports the "saw-teeth" like distribution of reactions is observed, and the more supports will be installed, the larger in absolute value reactions will arise.

The optimization problem is defined as in (Belevičius and Šešok 2008)

$$\min_{x\in D} f(x). \quad (1)$$

Here $f(x)$ is the objective function, D is the feasible shape of structure, which is defined by the type of certain supports, the given number and layout of different cross-sections as well as different materials in the structure.

$f(x)$ is defined by the maximum difference between vertical reactive force at a support and allowable reaction for this support, thus allowing us to achieve different reactions at supports on different beams, or even at particular supports on the same beam:

$$f(x) = \max_{x\in D} \max_{1\le i\le N_i} \left|R_i - c_i R_{allow}\right|. \quad (2)$$

Here N_s denote the number of supports, R_{allow} is allowable reaction, c_i are factors to this reaction and R_i are reactive forces in each support.

The values of objective function are defined by a finite element program.

Finite element matrices and sensitivity analysis.

The problem has to be solved in statics and in linear stage

$$[K]\{u\} = \{F\}. \quad (3)$$

Here $[K]$ is the stiffness matrix of grillage, $\{u\}$ are the displacements of grillage nodes, and $\{F\}$ – the loadings. The reactive forces at a rigid supports are obtained using equation

$$R_i = \sum_j K_{ij} u_j,\ i = 1,2,...,N_s, \quad (4)$$

where a part of nodal displacements (displacements of free nodes) are already obtained via (3), and the displacements of nodes representing the rigid supports are specified (usually – zero). If the supports have finite stiffness k_i,

$$R_i \approx k_i u_i,\ i = 1,2,...,N_s. \quad (5)$$

The sensitivity analysis that is required for the local search around the certain optimization solution is performed using the pseudo-load approach; thus, the numerical calculation of derivatives can be avoided. Denoting the support positions by $x_i, i = 1,2,...,N_s$

$$R_{i,x_i} = [K]_{,x_i}\{u\} + [K]\{u\}_{,x_i}. \quad (6)$$

Here the derivative of stiffness matrix is obtained analytically, while the derivative of displacements supposes solution of the general sensitivity equation:

$$[K]\{u\}_{,x_i} = \{F\}_{,x_i} - [K]_{,x_i}\{u\}. \quad (7)$$

The derivatives of load vector are obtained also in a closed form, analytically.

A simple two-node beam element with 6 d.o.f.'s at a node (three displacements and three rotations about local element axes) is employed in the analysis. Algorithms defining elements of stiffness matrix are well known, for example, in (Zienkiewicz and Taylor 2005). Additional details about finite element matrices are provided in (Belevičius and Šešok 2008).

Program. The finite element mesh of grillage is prepared automatically by the pre-processor, introducing nodes at support points, discontinuities of material and cross-sections properties, etc.

3. Choice of optimization algorithm

Genetic Algorithms (Goldberg 1989) are common tools in solving of optimization problems (Aliawdin and Kasabutski 2009; Amirjanov 2006, 2008; Chan *et al.* 2009). In our previous research (Belevičius and Šešok 2008; Šešok and Belevičius 2008) GA were applied for medium sized problems.

One more popular algorithm for stochastic optimization (Baumann 2008; Calafiore and Dabbene 2008) is Simulated Annealing (Lamberti and Pappalettere 2007; Lamberti 2008; Genovese *et. al.* 2005). In this paper

Simulated Annealing algorithm, is compared with GA using the same test problems. The results of SA happen to be better therefore SA was applied to a real life problem of 55 piles. Clustering of calculations was needed to accomplish the task in reasonable time.

4. Simulated Annealing algorithm

Setting SA parameters. Efficiency of SA depends on parameters such as initial temperature x_1 and annealing rate x_2. On the basis of numerical experiments the following parameter values were fixed in this research: $x_1 = 5.0$ and $x_2 = 2.0$.

Generating initial decision
The asymptotic results of SA are independent on initial decisions. However, the results of SA after finite number of iterations depend on these decisions. Therefore, to improve the results, the initial decisions were performed *N_init* times by random generation of piles coordinates and by selecting the best one. The minimal distance between piles $d_{\min}$ was limited by a half of grillage length divided by the number of piles. This limit is ignored during SA optimization because the real engineering limits of minimal distance between piles are not as great.

Generating permutations. The final SA results depend on the strategy of permutations.

The permutations were generated by adding a random number uniformly distributed in an interval $[-a_1, a_1]$. After N_1 iterations the interval was changed to the shorter one $[-a_2, a_2]$, were $a_2 < a_1$, and the remaining N_2 iterations were performed. This is the simplest version. In the following examples, the permutation interval was changed 4 times.

Selecting next decision. The permutation is accepted with probability $P_j = 1$, if it is better comparing with the current decision. Otherwise, it will be accepted, too, but with lesser probability $P_j = e^{\frac{\Delta f \ln(1+jx_2)}{x_1}}$. Here x_1 is the initial temperature, x_2 is the annealing rate, j is iteration number, and Δf is the difference between the current and permuted grillages.

5. Testing SA

To compare SA results with the results of GA (Belevičius and Šešok 2008) the same two test problems (10 and 15 piles) were investigated. The same numbers of 4000 iterations for 10-pile grillage and 9000 iterations for 15-pile grillage were fixed. The GA parameters (population size, mutation and crossover probabilities), as in case of SA parameters, also were chosen experimentally (see Belevičius and Šešok 2008) *The first test:* grillage of 10 piles. SA parameters are in Table 1.

SA and GA are stochastic algorithms therefore at least a couple of tens of numerical experiments should be accomplished for solution of each problem. Table 2 shows averages of 30 independent experiments.

Table 1. SA parameters (10 piles)

Initial temperature	5.0
Annealing rate	2.0
N_init	200
a_1	0.6
N_1	1000
a_2	0.2
N_2	1000
a_3	0.05
N_3	1000
a_4	0.01
N_4	800

Table 2. SA results (10 piles)

Sample	Value		Sample	Value
1	193.19		**16**	199.14
2	217.67		**17**	213.00
3	213.07		**18**	184.91
4	223.22		**19**	217.27
5	184.89		**20**	191.65
6	200.33		**21**	197.12
7	189.56		**22**	192.90
8	191.53		**23**	210.34
9	195.30		**24**	196.12
10	197.29		**25**	229.94
11	203.40		**26**	194.25
12	210.13		**27**	212.07
13	207.81		**28**	188.78
14	188.30		**29**	186.45
15	204.62		**30**	192.45

For illustration, an experiment using Intel(R) Xeon(R) CPU E5420 @ 2.50GHz 2.49 GHz, 3069 MB RAM, 32-bit requires 67 sec.

The best results are in Table 3.

Table 3. Best coordinates (10 piles)

Pile	X-position	Y-position
1	0.80	0.00
2	2.81	–3.00
3	5.48	–3.00
4	5.99	–6.00
5	9.97	–6.00
6	0.00	–5.47
7	4.00	–1.06
8	8.00	–1.76
9	8.00	–2.70
10	15.00	–0.99
Objective function	**184.89**	

Fig. 1 shows the graph of the decision shown in Table 3.

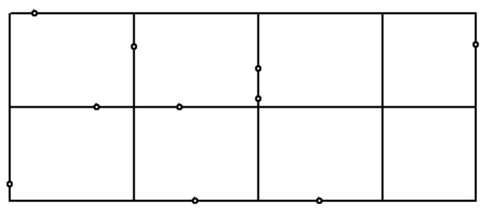

Fig. 1. Best decision (10 piles)

The second test: the grillage of 15 piles, 9000 iterations, the same as in (Belevičius and Šešok 2008). Table 4 shows SA parameters.

Table 4. SA parameters (15 piles)

Initial temperature	5.0
Annealing rate	2.0
N_init	400
a_1	0.6
N_1	2500
a_2	0.2
N_2	2500
a_3	0.05
N_3	2000
a_4	0.01
N_4	1600

Table 5 shows the average results of 30 independent samples.

Table 5. SA results (15 piles)

Nr. of sample	Value		Nr. of sample	Value
1	153.49		**16**	157.89
2	148.52		**17**	154.84
3	156.40		**18**	146.64
4	147.01		**19**	145.46
5	163.63		**20**	169.12
6	189.70		**21**	151.71
7	162.02		**22**	157.20
8	156.64		**23**	156.51
9	152.67		**24**	177.50
10	164.16		**25**	159.66
11	160.83		**26**	171.41
12	174.10		**27**	149.93
13	159.84		**28**	151.12
14	173.19		**29**	148.21
15	157.09		**30**	169.29

The average CPU time is 108 sec. for a test.

The coordinates of the best decision are in Table 6.

Table 6. Best coordinates (15 piles)

Pile	X-position	Y-position
1	7.38	0.00
2	11.76	0.00
3	1.68	–8.00
4	0.00	–4.39
5	0.00	–2.01
6	4.00	–2.02
7	4.00	–5.24
8	8.00	–5.07
9	8.00	–6.19
10	12.00	–7.09
11	12.00	–7.92
12	11.00	–13.60
13	15.00	–8.76
14	15.00	–12.52
15	13.45	–6.00
Objective function	**145.46**	

The graph of Table 6 decision is in Fig. 2.

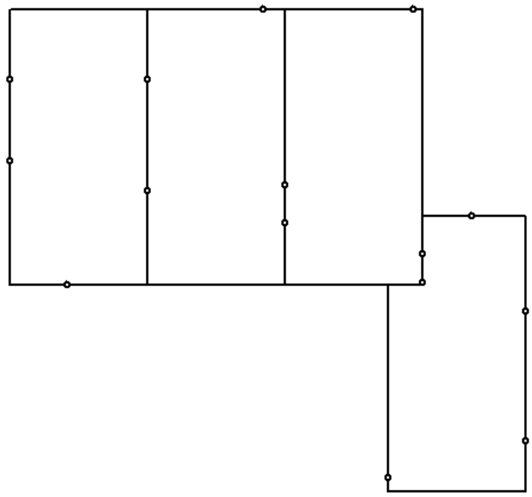

Fig. 2. Best decision (15 piles)

The results of GA and SA are compared in Table 7.

Table 7. Comparing SA with GA (10 and 15 piles)

Piles	Iterations	GA	SA	Global
10	4000	192.4	184.89	183.8
15	9000	157.7	145.46	143.0

In both the tests, SA did show better results.

In this research the optimal parameters of both GA and SA were defined heuristically, by experimental calculations. Automatic optimization of these parameters, for example, using the Bayesian Heuristic Approach (Mockus 2002), is an interesting subject of future research.

6. Real life grillage

SA is applied to optimize coordinates of 55 piles of complex configuration. First, the SA parameters defined in Table 4 are used. The results of 30 independent samples are in Table 8.

Table 8. SA results (55 piles, 9000 iterations)

Sample	Value		Sample	Value
1	565.84		**16**	665.23
2	667.26		**17**	584.83
3	467.89		**18**	668.10
4	665.66		**19**	556.77
5	468.29		**20**	466.44
6	613.68		**21**	674.08
7	497.41		**22**	673.89
8	493.48		**23**	480.65
9	560.79		**24**	589.95
10	618.61		**25**	486.33
11	606.26		**26**	563.89
12	616.41		**27**	551.77
13	577.93		**28**	544.18
14	473.97		**29**	499.86
15	537.22		**30**	546.72

The average CPU time is 3904 sec. for a test.

The results of the best decision 466.44 obtained after 9000 iterations differs from the global minimum 349.05 by 34%. This shows that we need more powerful computing environment.

7. Application of cluster

According to (Mockus 1967) asymptotic convergence rate is slow, not more than *log*(*N*), as usual, where *N* is the number of iterations. Theoretically, in order to decrease the discrepancy between obtained optimization result and the global solution twice, we have to perform about 100 times more iterations. Thus, for the 55-pile grillage we choose the number of iterations of 10^6.

To perform such a number of iterations a cluster of computers was applied. All computations were performed on the PC cluster VILKAS (Rocks Cluster Distribution v 5.0, CentOS release 5, x86_64) at Vilnius Gediminas Technical University. The cluster consisted of 18 PCs connected by Gigabit Ethernet (D-Link DGS 1224T Gigabit Smart Switch, 24-Ports 10/100/1000Mbps Base-T Module). Hardware characteristics of the PC are listed below: Intel® Core2Quad Q6600 2.40GHz CPU (2x4MB L2 cache and bus frequency equal 1067 MHz), 2x2GB DDR2 800 RAM, 300GB HDD (SATA II Extensions and 16 MB cache), Gigabit Ethernet NIC. 340 Gflop/s performance was measured running HPL benchmark. The average results of 40 independent samples for each of the cluster computers are in Table 10. The total CPU time was about 50 hours.

SA parameters for this test are in Table 9.

Table 9. SA parameters (55 piles)

Initial temperature	5.0
Annealing rate	2.0
N_init	500000
a_1	0.6
N_1	150000
a_2	0.2
N_2	150000
a_3	0.05
N_3	100000
a_4	0.01
N_4	100000

The results are in Table 10.

Table 10. SA results (55 piles, 1.000.000 iterations)

Sample	Value		Sample	Value
1	426.88		**21**	467.01
2	388.64		**22**	423.25
3	421.98		**23**	463.05
4	455.17		**24**	468.59
5	429.52		**25**	480.05
6	464.72		**26**	418.57
7	408.67		**27**	423.29
8	425.45		**28**	462.71
9	440.74		**29**	420.65

Continue of Table 10

Sample	Value		Sample	Value
10	461.86		**30**	441.54
11	417.97		**31**	455.12
12	488.54		**32**	417.27
13	458.99		**33**	403.18
14	456.22		**34**	416.97
15	458.31		**35**	457.97
16	457.55		**36**	385.15
17	462.85		**37**	430.81
18	417.69		**38**	460.69
19	397.27		**39**	460.87
20	379.35		**40**	461.78

The best result (379.35) differs from global minimum (349.05) by 9%. Thus, this error is better than the theoretical estimation of error for the number of iterations performed. This is acceptable error. Figure 3 shows the graph of this decision.

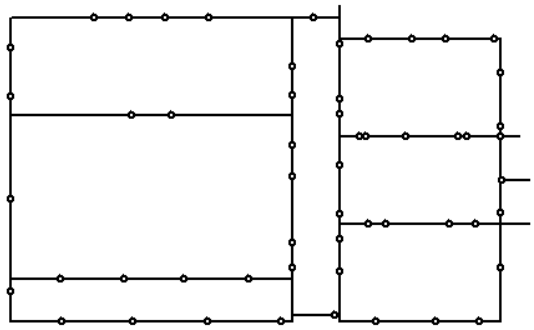

Fig. 3. Best decision (55 piles, 10^6 iterations)

Here are the coordinates of the best obtained solution:
(12.34, –30.35); (19.85, –30.35); (27.17, –30.35); (8.40, 0.00); (11.96, 0.00); (15.56, 0.00); (19.93, 0.00); (30.40, 0.00); (32.52, –29.73); (5.09, –26.03); (11.40, –26.03); (17.44, –26.03); (23.97, –26.03); (12.14, –9.71); (16.18, –9.71); (36.65, –30.35); (42.64, –30.35); (47.12, –30.35); (35.88, –20.59); (37.71, –20.59); (44.11, –20.59); (46.69, –20.59); (35.07, –11.87); (35.70, –11.87); (39.64, –11.87); (44.93, –11.87); (45.80, –11.87); (35.91, –2.11); (40.28, –2.11); (43.73, –2.11); (48.59, –2.11); (0.00, –27.28); (0.00, –18.04); (0.00, –7.84); (0.00, –2.96); (28.32, –25.00); (28.32, –22.42); (28.32, –15.76); (28.32, –12.63); (28.32, –7.74); (28.32, –4.78); (33.04, –25.33); (33.04, –22.07); (33.04, –19.61); (33.04, –14.75); (33.04, –9.57); (33.04, –8.06); (33.04, –2.54); (49.24, –24.88); (49.24, –19.40); (49.24, –11.80); (49.24, –10.84); (49.24, –5.44); (49.35, –16.23).

The data and the FORTRAN library for calculation of objective function are on the web (Mockus 2006):
http://soften.ktu.lt/~mockus/grillage/contgrillage.html

- Data10.dat is for 55 piles ,
- Data11.dat is for 10 piles,
- Data12.dat is for 15 piles,
- Grillage.lib is the Windows library with subroutines for calculation of objective function.
- Example.f90 is the FORTAN example file.

8. Conclusions

In the medium sized (10–15 piles) test examples SA did show better results comparing with GA. Using the same number of iterations, the SA deviations from the global minimum for 10- and 15-pile grillages were about 8 and 6 times less, correspondingly. Parameters of both algorithms were adapted by additional experimentation calculations ended in reasonable time using standard PC.

Solving a real life example (55 piles) clustering was used. For larger examples, the search algorithms should be optimized and specific features of the problem exploited.

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GLOBALUS ROSTVERKŲ OPTIMIZAVIMAS TAIKANT ATKAITINIMO MODELIAVIMO METODĄ IR REMIANTIS DIDELIO NAŠUMO SKAIČIAVIMAIS

D. Šešok, J. Mockus, R. Belevičius, A. Kačeniauskas

S a n t r a u k a

Straipsnio tikslas – ištirti galimus rostverkinių pamatų optimizavimo būdus. Siekiant šio tikslo du gerai žinomi optimizavimo metodai – genetiniai algoritmai ir atkaitinimo modeliavimo algoritmas – buvo palyginti vidutinio dydžio (10 ir 15 polių) pavyzdžiams išspręsti. Tikslo funkcija imama didžiausia atraminė poliaus reakcija. Projektavimo kintamieji – polių koordinatės. Atkaitinimo modeliavimo metodas laimi, todėl jis buvo pritaikytas praktiniam uždaviniui (55 poliai) spręsti. Spręsti buvo naudojamas klasteris. Naujumas – genetinių algoritmų palyginimas su atkaitinimo modeliavimo metodu bei atkaitinimo modeliavimo metodo pritaikymas sprendžiant praktinį uždavinį.

Reikšminiai žodžiai: rostverkai, atkaitinimo modeliavimas, globalus optimizavimas, baigtiniai elementai, genetiniai algoritmai.

Dmitrij ŠEŠOK. Postdoctoral Researcher at the Systems Analysis Department. Institute of Mathematics and Informatics, Dr Assoc Professor at the Dept of Engineering Mechanics. Vilnius Gediminas Technical University, Lithuania. Research interests: global optimization of mechanical structures.

Jonas MOCKUS. Prof. Dr Habil. Systems Analysis Department. Institute of Mathematics and Informatics, Lithuania. Research interests: global optimization.

Rimantas BELEVIČIUS. Prof. Dr Habil. Head of Dept of Engineering Mechanics, Vilnius Gediminas Technical University, Lithuania. Research interests: global optimization, finite element method.

Arnas KAČENIAUSKAS. Dr, Assoc Professor, Head of Laboratory of Parallel Computing, Vilnius Gediminas Technical University, Lithuania. Research interests: high performance computing.