Prediction of Ultimate Soil Bearing Capacity for Shallow Strip Foundation on Sandy Soils Using (ANN) Technique

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ABSTRACT

Bearing capacity of soil is an important factor in designing shallow foundations. It is directly related to foundation dimensions and consequently its performance.

The calculations for obtaining the bearing capacity of a soil needs many varying parameters, for example soil type, depth of foundation, unit weight of soil, etc. which makes these calculation very variable–parameter dependent.

This paper presents the results of comparison between the theoretical equation stated by Terzaghi and the Artificial Neural Networks (ANN) technique to estimate the ultimate bearing capacity of the strip shallow footing on sandy soils. The results show a very good agreement between the theoretical solution and the ANN technique.

Results revealed that using ANN gave a very high correlation factor associated with the results obtained from Terzagih's equation, besides little computation time needed compared with computation time needed when applying Terzagih's equation.

الخلاصة

قابلية تحمل التربة للأحمال من العوامل المهمة التي نحتاجها في تصميم الأسس الضحلة لما لها من تأثير على أبعاد التصميم وبالتالي على أدائه بشكل مباشر.

ان عملية احتساب تحمل التربة تحتاج إلى عدة عوامل وتشمل متغيرات كثيرة مثل نوع التربة، عمق الأساس، وحدة الوزن للتربة، ...الخ. مما يجعل احتساب تحمل التربة من المقادير المتغيرة بشكل كبير تبعا للعوامل المذكورة.

لهذا تم تصميم موديل باستخدام الشبكات العصبية لحساب قابلية تحمل التربة يغني عن اجراء الحسابات المعقدة وتمت المقارنة بين نتائجها والنتائج المستحصلة من استخدام المعادلات النظرية حيث اظهرت النتائج توافق كبير جدا فيما بينها يضاف الى ذلك التوفير الكبير في الوقت اللازم لاجراء الحسابات باستخدام طريقة الشبكات العصبية مقارنة مع الطرق التقليدية.

Keyword: Soil Bearing capacity, Artificial Neural Network, shallow foundation.

1. INTRODUCTION

The ultimate bearing capacity for a soil q_u is defined as the least pressure which would cause shear failure of the supporting soil immediately below and adjacent to a foundation.

The ultimate bearing capacity can be determine either experimentally or by calculations using analytical and / or empirical formulae.

Artificial Neural Network (ANN) technique became a powerful tool that can be used to solve the civil engineering problems (Jeng, et al., 2003), and a more effective tool for engineering applications, thus this study was undertaken in order to predict the ultimate bearing capacity of shallow strip footing over sandy soil by using artificial neural networks technique.

A set of varying conditions are studied and the results obtained by implementing the artificial neural network technique are then compared to the results obtained by implementing Terzaghi's equation, results revealed a very high correlation factor between answers obtained from implementing the ANN technique and the answers obtained by implementing Terzagi’s equation.

2. Theory

The ultimate bearing capacity of the soil under shallow strip footing can be expressed by the following general equation, Terzaghi (1943).See Figure (1).

$$\mathbf{q_u = c\, N_c + \gamma\, D\, N_q + 0.5\, B\, \gamma\, N_\gamma} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

where c = Cohesion of soil.

γ = Unit weight of soil.

D = Footing depth.

B = Footing width.

$\mathbf{N_c}$, $\mathbf{N_q}$, $\mathbf{N_\gamma}$ = bearing capacity factors depending only on (ϕ)

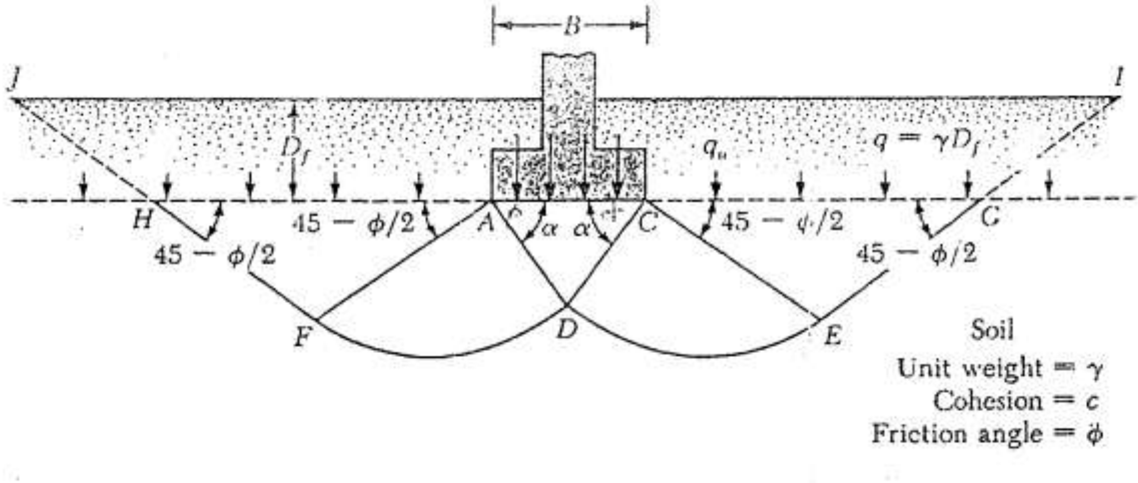
$$\mathbf{N_c} = (\mathbf{N_q} - 1)\cot\phi \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (2)$$

$$\mathbf{N_q} = e^{(\pi \tan\phi)} \tan^2\left(45 + \frac{\phi}{2}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3)$$

$$\mathbf{N_\gamma} = 2\,(N_q + 1)\tan\phi \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

ϕ = Angle of internal friction of the soil.

Eq.(2) for $\mathbf{N_c}$ was originally derived by Prandtl (1921),and Eq.(3) for $\mathbf{N_q}$ was presented by Reissner (1924). Caquot and Kerisel (1953) and Vesic (1973) gave the relation for $\mathbf{N_\gamma}$ (Eq.(4)).



Figure(1)
Failure surface of shallow foundation

3. Implementation of Neural Network

MatLab version R2008a was used in designing and implementation of the ANN (Demuth, et al., 2008). To find the most appropriate design and learning algorithm, the method of trial and error was used by choosing different learning algorithms, layers, and neurons, as follows (Zurada, 1992):

1. Ten different learning algorithms were used presented in Appendix (A) Table A–1.
2. Three different numbers of layers were used, 1 layer, 2 layers, and 3 layers.
3. Three different numbers of neurons were used, 10, 20, and 30 neurons per each layer.

First, Eq. (1) was used to calculate the ultimate bearing capacity for various soil properties, considering different values for the parameters needed to solve the equation, as follows:

1. ϕ varying from 10° to 45°, steps of 2.5° was used.
2. γ varying from 14 kN/m^3 to 23 kN/m^3 steps of 1.0 kN/m^3 was used.
3. B varying from 0.5 m to 1.5 m , steps of 0.1 m was used.
4. D varying from 0.5 m to 1.5m, steps of 0.25 m was used.
5. c = 0 for sandy soil.

Practically, these values could represent and cover the actual range that may be needed in the analysis and design of real problems. The sum of 8250 cases were taken into consideration, each case represents a different design alternative and has a unique ultimate bearing capacity value. The ultimate bearing capacity was calculated for each case using Eq.1 as mentioned before.

All these cases and their parameters are considered as the input data for a special ANN designed to memorize each individual case and its calculated bearing capacity so that it could predict the ultimate bearing capacity later.

A procedure of trial and error was used to find the most appropriate number of layers, number of neurons per layer, and the most efficient learning algorithm among ten learning algorithms implemented in teaching the Neural Networks.

Another set of random data was prepared to verify the reliability and the consistency of the Neural Network, the data were totally different from the input data and there values were never shown in the input data.

This procedure was conducted to obtain the most efficient Neural Network which is considered to have:

1. maximum correlation ratio between the target data and the output data obtained,
2. maximum correlation ratio between verifying data and the output obtained, and
3. minimum time to reach solution.

4. Results and Discussion

Table A-2 represents a sample of the first 100 input data (Appendix-A) , the total number of data inputs were 2640. The method of trial and error was used to find the most appropriate Neural Network that can reflect the most suitable design requirements (i.e. the correct ultimate bearing capacity q_u for the required design parameters, ϕ, D, B, γ, and c).
Among ten learning algorithms, ten outputs were obtained, each output was obtained after teaching the Neural Network with the most representative number of neurons, and number of layers. A correlation factor was calculated for each output to show the reliability of the network.
Table(1) shows the algorithm name and the highest correlation factor that can be obtained after applying the learning rule for a variety of neuron numbers and layers.

Table 1 Algorithm name vs. correlation factor

No.	Algorithm name	Correlation Factor	Neuron numbers And Number of Layers
1	GDA	0.995057444	10
2	GDX	0.997960736	10 x 10
3	RP	0.999956575	20
4	CGF	0.999120732	10
5	CGP	0.998901795	10 x 10
6	LM	0.999999993	10
7	BFG	0.997986589	10
8	SCG	0.999295558	10
9	CGB	0.996573746	10
10	OSS	0.997773765	10

As can be seen from Table 1, the most efficient algorithm that gave the highest correlation factor is no. 6 (LM learning rule) with 10 neurons (i.e. one layer which consist of 10 Neurons) with a correlation factor of 0.999999993.
Table 2 shows the verifying data that was used to test each algorithm and its corresponding Neural Network, the input data were chosen so that they were never taught to the Neural Network before (they were never shown in the input data that was used for teaching the network in the first step).

Table 2 Verifying Data Used to Test Reliability of Neural Network

No.	B	γ	D	ϕ	q_u	Output
1	0.75	19.1	1.1	18	139.589	139.5673802
2	0.8	22	0.87	29	484.899	484.7750421
3	1.1	15.86	0.57	41	1803.897	1804.095986
4	1.3	18.2	0.97	38	1786.895	1786.784995
5	1.45	22.5	0.76	14	98.61363	98.64410774
6	1.15	15.73	0.81	32	568.5862	568.6354125
7	0.88	16.6	1.49	19	177.5926	177.4755966
8	1.22	21.5	0.55	27	345.8494	345.9459282
9	1.45	15.66	1.3	17	137.223	137.1086517
10	1.55	19.24	0.73	42	3518.381	3518.516495
11	0.22	14.3	0.56	34	300.3472	299.7223238
12	0.38	20.1	1.44	22	253.5961	253.7477964
13	1.11	17.8	0.61	44	3471.177	3471.39989
14	0.93	20.5	0.88	11	62.64117	62.45822203
15	0.67	21	0.59	37	997.4388	997.6196914
16	0.4	13.5	1.45	19.8	136.9498	137.127496
17	0.3	17.6	1.1	33.2	613.1835	612.9913123
18	1.45	15	0.3	9.5	22.8533	22.84814129
19	1	13	0.68	43.4	2235.155	2235.190448
20	1.4	12	0.25	15.6	36.78086	36.3282789

The output was then compared to the calculated values using the same formula (Eq. 1) and a correlation factor is evaluated the see the most efficient algorithm that gave the highest correlation factor for the test data. Results are shown in Table 3.

Table 3 Correlation Factor Obtained for Each Learning Algorithm

No.	Algorithm Name	Correlation Factor
1	GDA	0.997409464
2	GDX	0.998322484
3	RP	0.999934347
4	CGF	0.999094581
5	CGP	0.999188115
6	LM	0.999999984
7	BFG	0.998235235
8	SCG	0.997448906
9	CGB	0.993152833
10	OSS	0.997531545

As could be seen from Table 3 that the algorithm that gave the best correlation factor is no. 6 (LM) with a correlation factor of 0.999999984.

Figure 2 shows the performance of the Neural Network reflected by showing the Mean Squared error (MSE) of value less than 0.01.

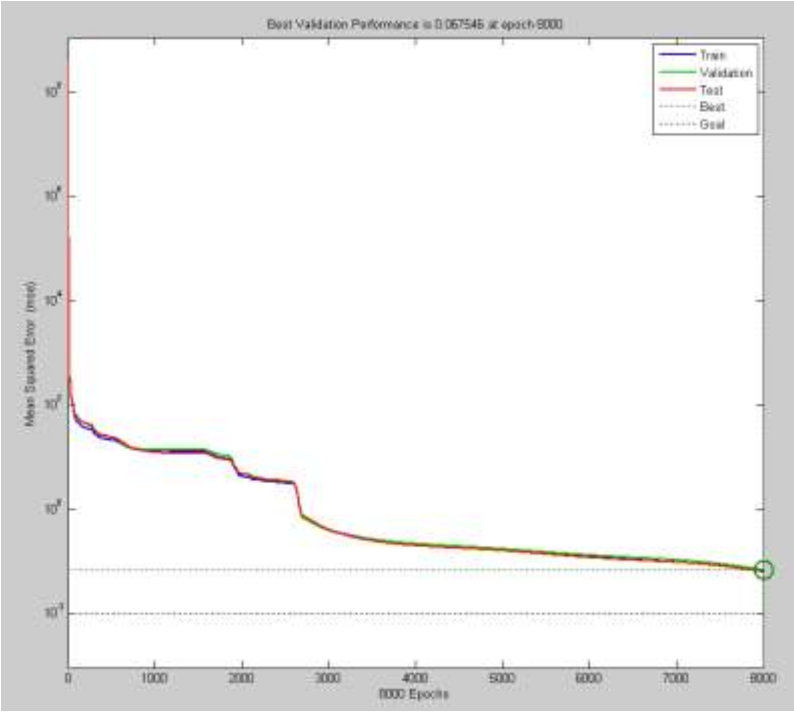


Figure (2)
Performance of the trained Neural Network

Where Figure. 3 shows the regression value obtained after training the Neural Network which shows a value of (1) which means that the output obtained have a very strong relation to the target values desired.

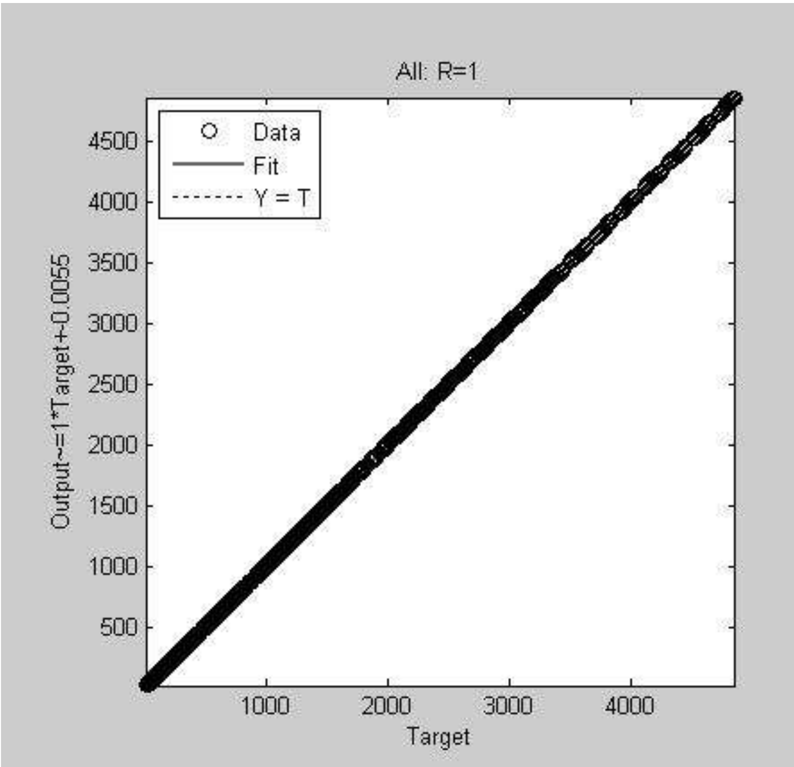


Figure (3)
Regression Value of Neural Network
Between Input Data and Target Data

5. Conclusions and recommendations

The calculation of bearing capacity of shallow foundation is a many parameter dependant process, and it has many pre calculations till we can implement the Terzaghi's equation (Eq. 1), these calculations include the bearing capacity factors N_q, N_γ, and N_c. Another alternative is to use the charts which could lead to some approximations.

Using an Artificial Neural Network can facilitate these calculations to a great extent. The Neural Network can remember the parameters that were used as an input (B, D, ϕ, c, and γ) and the calculated values of the ultimate bearing capacity q_u, and this operation has to be done only once, then the network can be used to predict the bearing capacity for any input values and give the bearing capacity value as was done here by using the verifying data.

The advantage of using the Artificial Neural Network comes mainly from saving calculation time of the parameters and the ultimate bearing capacity, and once the network was ready, the same network can be used as many times as desired with no further need for teaching or modifying, besides, the calculation needed when using the Neural Network are simple compared to the calculations needed to obtain the results in the original equation.

6. References

- Caquot, A. and Kerisel, J. 1953. Surle le Terme de Surface dans le Calcul des Fondations en Milieu Pulverulent. Proceedings of the 3rd International Conference on Soil Mechanics and Foundation Engineering. Vol. 1, pp. 336-337 (as cited by Cerato, A.B. and Lutenegger, A.J., 2007, "Scale Effects of Shallow Foundations Bearing Capacity on Granular" , Journal of Geotechnical and Geoenvironmental Engineering, ASCE, Vol. 133, No. 10, pp. 1192-1202).
- Demuth, H., Mark B., and Martin H., 2008, " Neural Network Toolbox™ 6 User's Guide", The MathWorks, Inc.
- Jeng, D.S., Cha D. H. and Blumenstein M., 2003, "Application of Neural Network in Civil Engineering Problems", Proceedings of the International Conference on Advances in the Internet, Processing, Systems and Interdisciplinary Research (IPSI-2003).
- Prandtl, L. (1921). Uber Die Eindringungsfestigkeit (Harte) Plastischer Baustoffe Und Die Festigkeit Von Schneiden. Zeitschrift fur angewandte Mathematik und Mechanik. Vol. 1, No. 1. pp. 15-20 (as cited by Lee, J. H. and Salgado, R., 2005, "Estimation of Bearing Capacity of Circular Footings on Sands Based on Cone Penetration Test " , Journal of Geotechnical and Geoenvironmental Engineering, ASCE, Vol. 131, No. 4, pp. 442-452).
- Reissner, H. (1924). "Zum Erddruckproblem" (Concerning the earth-pressure problem), Proc. 1st Int. Congress of Applied Mechanics, Delft, pp. 295-311 (as cited by Lee, J. H. and Salgado, R., 2005, "Estimation of Bearing Capacity of Circular Footings on Sands Based on Cone Penetration Test", Journal of Geotechnical and Geoenvironmental Engineering, ASCE, Vol. 131, No. 4, pp. 442-452).
- Terzaghi,K., 1943,"Theoretical Soil Mechanics",John Wiley and Sons,New York.
- Vesic, A. S., 1973., "Analysis of Ultimate Loads of Shallow Foundation", Journal of Soil Mechanics and Foundations Division, American Society of Civil Engineers ,Vol.99 , No.SM1,pp.45-73.
- Zurada, J. M., 1992, "Introduction to Artificial Neural Systems", PWS Publishing Company.

Appendix A

Table A–1 Training Algorithms Names and Symbols

Symbol	Algorithm Name
GDA	Backpropagation training with an adaptive learning rate
GDX	adaptive learning rate with momentum training
RP	Resilient Backpropagation
CGF	Fletcher-Powell Conjugate Gradient
CGP	Polak-Ribiére Conjugate Gradient
LM	Levenberg-Marquardt
BFG	BFGS Quasi-Newton
SCG	Scaled Conjugate Gradient
CGB	Conjugate Gradient with Powell/Beale Restarts
OSS	One Step Secant

Table A-2 Sample of 100 Input Data and Output Data

B (m)	γ kN/m^3	D (m)	ϕ Degree	q_u kN/m^2	output
0.5	14	0.5	10	21.5848	21.22723
0.6	14	0.5	10	22.44175	22.131557
0.7	14	0.5	10	23.29871	23.036521
0.8	14	0.5	10	24.15566	23.942056
0.9	14	0.5	10	25.01261	24.848096
1	14	0.5	10	25.86956	25.754572
1.1	14	0.5	10	26.72651	26.661415
1.2	14	0.5	10	27.58346	27.568553
1.3	14	0.5	10	28.44041	28.475913
1.4	14	0.5	10	29.29736	29.38342
1.5	14	0.5	10	30.15431	30.290999
0.5	15	0.5	10	23.12658	22.701227
0.6	15	0.5	10	24.04474	23.669899
0.7	15	0.5	10	24.9629	24.639469
0.8	15	0.5	10	25.88106	25.609868
0.9	15	0.5	10	26.79922	26.581027
1	15	0.5	10	27.71738	27.552874
1.1	15	0.5	10	28.63555	28.525336
1.2	15	0.5	10	29.55371	29.498339
1.3	15	0.5	10	30.47187	30.471805
1.4	15	0.5	10	31.39003	31.445657
1.5	15	0.5	10	32.30819	32.419815
0.5	16	0.5	10	24.66835	24.174608
0.6	16	0.5	10	25.64772	25.208604
0.7	16	0.5	10	26.62709	26.243726
0.8	16	0.5	10	27.60646	27.279905
0.9	16	0.5	10	28.58584	28.317065
1	16	0.5	10	29.56521	29.355131
1.1	16	0.5	10	30.54458	30.394026
1.2	16	0.5	10	31.52395	31.433671
1.3	16	0.5	10	32.50333	32.473987
1.4	16	0.5	10	33.4827	33.514889
1.5	16	0.5	10	34.46207	34.556294
0.5	17	0.5	10	26.21012	25.677576
0.6	17	0.5	10	27.2507	26.777482
0.7	17	0.5	10	28.29129	27.878705
0.8	17	0.5	10	29.33187	28.981169
0.9	17	0.5	10	30.37245	30.084795
1	17	0.5	10	31.41303	31.189503
1.1	17	0.5	10	32.45362	32.295211
1.2	17	0.5	10	33.4942	33.401837
1.3	17	0.5	10	34.53478	34.509294
1.4	17	0.5	10	35.57537	35.617494
1.5	17	0.5	10	36.61595	36.726348
0.5	18	0.5	10	27.75189	27.218992
0.6	18	0.5	10	28.85368	28.384881
0.7	18	0.5	10	29.95548	29.552236
0.8	18	0.5	10	31.05727	30.720975
0.9	18	0.5	10	32.15907	31.891015
1	18	0.5	10	33.26086	33.062271
1.1	18	0.5	10	34.36265	34.234655
1.2	18	0.5	10	35.46445	35.408079
1.3	18	0.5	10	36.56624	36.582451
1.4	18	0.5	10	37.66804	37.757677
1.5	18	0.5	10	38.76983	38.933664
0.5	19	0.5	10	29.29366	28.788127
0.6	19	0.5	10	30.45667	30.019713
0.7	19	0.5	10	31.61967	31.252875
0.8	19	0.5	10	32.78268	32.487525
0.9	19	0.5	10	33.94568	33.723576
1	19	0.5	10	35.10869	34.960935
1.1	19	0.5	10	36.27169	36.19951
1.2	19	0.5	10	37.4347	37.439205
1.3	19	0.5	10	38.5977	38.679923
1.4	19	0.5	10	39.7607	39.921564
1.5	19	0.5	10	40.92371	41.164027
0.5	20	0.5	10	30.83543	30.363828
0.6	20	0.5	10	32.05965	31.660667
0.7	20	0.5	10	33.28386	32.959154
0.8	20	0.5	10	34.50808	34.259197
0.9	20	0.5	10	35.7323	35.560699
1	20	0.5	10	36.95651	36.863564
1.1	20	0.5	10	38.18073	38.167692
1.2	20	0.5	10	39.40494	39.472979
1.3	20	0.5	10	40.62916	40.779322
1.4	20	0.5	10	41.85337	42.086614
1.5	20	0.5	10	43.07759	43.394744
0.5	21	0.5	10	32.37721	31.922273
0.6	21	0.5	10	33.66263	33.283877
0.7	21	0.5	10	34.94806	34.647164
0.8	21	0.5	10	36.23348	36.012033
0.9	21	0.5	10	37.51891	37.378382
1	21	0.5	10	38.80434	38.746104
1.1	21	0.5	10	40.08976	40.115094
1.2	21	0.5	10	41.37519	41.48524
1.3	21	0.5	10	42.66062	42.856431
1.4	21	0.5	10	43.94604	44.22855
1.5	21	0.5	10	45.23147	45.60148
0.5	22	0.5	10	33.91898	33.440565
0.6	22	0.5	10	35.26561	34.866431
0.7	22	0.5	10	36.61225	36.293971
0.8	22	0.5	10	37.95889	37.723078
0.9	22	0.5	10	39.30553	39.153639
1	22	0.5	10	40.65216	40.585541
1.1	22	0.5	10	41.9988	42.018669
1.2	22	0.5	10	43.34544	43.452902
1.3	22	0.5	10	44.69207	44.88812
1.4	22	0.5	10	46.03871	46.324198
1.5	22	0.5	10	47.38535	47.76101
0.5	23	0.5	10	35.46075	34.897374