Application of the Adaptive Neuro Fuzzy Inference System (ANFIS) to Predict Ultimate Bearing Capacity of Footing on Granular Soil

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Abstract. The ultimate bearing capacity is an important parameter in the footing foundation design. Several classical methods are often used to analyze the bearing capacity of a footing foundation. However, the results of this analysis always give less accurate results than the experiment. In this manuscript, an Adaptive Neuro Fuzzy Inference System (ANFIS) model was built for predicting ultimate bearing capacity of footings on granular soil. Learning process data consists of input and output. The five input parameters used for the model development in this study are width (B), depth (D_f), shape factor (L/B) of footing, unit weight (γ) and friction angle (ϕ) of soil and the output is ultimate bearing capacity (q_u). The results of the analysis showed that the ANFIS model has a good level of accuracy compared with the experiment, where the correlation coefficient (R^2) for testing data was 0.98 and the Root Mean Square Error (RMSE) was 32.11 kN/m^2. This demonstrates that the ANFIS model developed is accurate in predicting the ultimate bearing capacity of footings on granular soil.

Keywords: footing · granular soil · ultimate bearing capacity · ANFIS

1 Introduction

Footing is one type of shallow foundation that is widely used in reinforced concrete building structures. The ultimate bearing capacity is an essential requirement for foundation design. Several classical methods are often used to analyze the bearing capacity of foundations, namely the theories of Terzaghi, Meyerhof, Vesic [1–3] and others. However, the results of this analysis always give less accurate results than the experiment. This is due to the uncertain nature of the soil and the difficulty of experimental testing in the laboratory and in situ, so it is necessary to look for alternative bearing capacity prediction methods to obtain more accurate results.

The development of soft computing, especially in the field of artificial intelligence, enables computer machines to solve problems such as those done by humans. Some artificial intelligence which has been applied in the field of civil engineering is artificial neural networks (ANN) and fuzzy logic (FL) [4]. However, the use of the ANN method has several weaknesses, namely It takes a lot of iterations in the training process to process

B. Anshari et al. (Eds.): MIMSE-C-A 2022, AER 215, pp. 3–14, 2023.
https://doi.org/10.2991/978-94-6463-088-6_2

the neural network, so sometimes the results obtained become less accurate. While the weakness in the fuzzy logic (FL) method requires an optimization method, namely by how to try (trial and error) in determining the membership function to obtain an optimal membership function. Hence, by combining ANN and FL methods into the Adaptive Neuro Fuzzy Inference System method (ANFIS), where membership functions and rules (IF THEN) can be determined from data input automatically through the learning process, this model is expected to be able to reduce the weaknesses of each method, so that the predictions generated will be more accurate. In this study, the ANFIS method has been used for predicting the ultimate bearing capacity of a footing on granular soil.

2 Theory

2.1 Ultimate Bearing Capacity

The highest resistance to pressure applied through the foundation to the soil without causing shear failure in the soil may be considered the ultimate bearing capacity of the soil. Terzaghi was the first to introduce a theory for estimating the ultimate bearing capacity of shallow foundations. He invented the following semi-empirical equation to express the ultimate bearing capacity of a strip footing [5]:

$$q_u = c\,Nc\left(1 + 0.3\frac{B}{L}\right) + D_f\,\gamma\,N_q + 0.5\,\gamma\,B\,N_\gamma\left(1 - 0.2\frac{B}{L}\right) \tag{1}$$

$$N_c = \text{cotg}\,\phi\left(\frac{a^2}{2\cos^2(45 + \phi/2)} - 1\right) \tag{2}$$

$$N_q = \left(\frac{a^2}{2\cos^2(45 + \phi/2)} - 1\right)N_c\,\text{tg}\,\phi + 1 \tag{3}$$

$$N_\gamma = \left(\frac{\text{tg}\,\phi}{2}\right)\left(\frac{K_{p\gamma}}{\cos^2\phi} - 1\right) \tag{4}$$

$$a = e^{\left(\frac{3}{4}\pi - \frac{\phi}{2}\right)\text{tg}\,\phi} \tag{5}$$

$$K_{p\gamma} = 3\tan^2\left[45^\circ + \frac{1}{2}(\phi + 33^\circ)\right] \tag{6}$$

where:
q_u: ultimate bearing capacity (kN/m^2)
N_c, N_q, N_γ: factors of bearing capacity
c: cohesion (kN/m^2)
φ: friction angel (^{o})
γ: unit weight of soil (kN/m^3)
$K_{p\gamma}$: passive earth pressure coefficient
B: width of footing foundation (m)
L: length of footing foundation (m)
D_f: depth of footing foundation (m)

2.2 Adaptive Neuro Fuzzy Inference System (ANFIS)

The Adaptive Neuro Fuzzy Inference System (ANFIS) was first introduced by Jang in 1993 [6], is a combination of Artificial Neural Network (ANN) and Fuzzy Inference System (FIS) that uses the Takagi and Sugeno model. By using a hybrid learning procedure (a combination of the Backward-Propagation Gradient Descent method (BPGD) and Least Squares Estimator (LSE), ANFIS can build a mapping input and output that is both based on human knowledge with fuzzy rules IF THEN with the right membership function. The modeling process with ANFIS Tools in MATLAB Student Version R2014a is divided into three parts, namely the training, testing, and checking process [7]. The principle of the training process is to learn about data in order to obtain results in accordance with the targets on the data. The testing process is the process of testing the accuracy of the models that have been obtained from the training process.

3 Research Methodology

3.1 Data Collection

Data collection must have been carried out prior to modeling. The ANFIS model was created utilizing data from previous research on the ultimate bearing capacity test, including Muhs et al.; Weiβ; Muhs and Weiβ; Briaud and Gibbens; Gandhi; Golder and Eastwood [8–15], also available in reference [5]. The obtained data is then grouped into data that will be input and output. There are 97 data series [8–13] for training (Table 1) and 9 data [14, 15] for the testing process (Table 2). The following five independent variables were treated as input data: width (B), depth (D_f), shape factor (L/B) of footing, unit weight of soil (γ) and friction angle (ϕ) of soil, while the output was the ultimate bearing capacity (q_u) of footing.

3.2 Performance ANFIS Model

To find out the reliability and the level of accuracy of the ANFIS model, the error value is calculated with the correlation coefficient (R^2) and Root Mean Square Error (RMSE) in Eqs. (7) and (8):

$$R^2 = 1 - \frac{\sqrt{\sum_{i=1}^{n}(t_i - y_i)^2}}{\sqrt{\sum_{i=1}^{n}(t_i - \bar{t})^2}} \tag{7}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(t_i - y_i)^2}{n}} \tag{8}$$

where:
t_i: experiment data i
y_i: ANFIS model data i
$\bar{t}$: average experiment data
n: number of data

Table 1. Data training.

No Data	B (m)	D_f (m)	L/B	γ (kN/m^3)	ϕ (°)	q_u (kN/m^2)	Ref.
1	0.6	0.3	2	9.85	34.9	270	[8]
2	0.6	0	2	10.2	37.7	200	
3	0.6	0.3	2	10.2	37.7	570	
4	0.6	0	2	10.85	44.8	860	
5	0.6	0.3	2	10.85	44.8	1760	
6	0.5	0	1	10.2	37.7	154	[9]
7	0.5	0	1	10.2	37.7	165	
8	0.5	0	2	10.2	37.7	203	
9	0.5	0	2	10.2	37.7	195	
10	0.5	0	3	10.2	37.7	214	
11	0.52	0	3.85	10.2	37.7	186	
12	0.5	0.3	1	10.2	37.7	681	
13	0.5	0.3	2	10.2	37.7	542	
14	0.5	0.3	2	10.2	37.7	530	
15	0.5	0.3	3	10.2	37.7	402	
16	0.52	0.3	3.85	10.2	37.7	413	
17	0.5	0	1	11.7	37	111	[10]
18	0.5	0	1	11.7	37	132	
19	0.5	0	2	11.7	37	143	
20	0.5	0.013	1	11.7	37	137	
21	0.5	0.029	4	11.7	37	109	
22	0.5	0.127	4	11.7	37	187	
23	0.5	0.3	1	11.7	37	406	
24	0.5	0.3	1	11.7	37	446	
25	0.5	0.3	4	11.7	37	322	
26	0.5	0.5	2	11.7	37	565	
27	0.5	0.5	4	11.7	37	425	
28	0.5	0	1	12.41	44	782	
29	0.5	0	4	12.41	44	797	[10]
30	0.5	0.3	1	12.41	44	1940	
31	0.5	0.3	1	12.41	44	2266	

(*continued*)

Table 1. (*continued*)

No Data	B (m)	D_f (m)	L/B	γ (kN/m^3)	ϕ (°)	q_u (kN/m^2)	Ref.
32	0.5	0.5	2	12.41	44	2847	
33	0.5	0.5	4	12.41	44	2033	
34	0.5	0.49	4	12.27	42	1492	
35	0.5	0	1	11.77	37	123	
36	0.5	0	2	11.77	37	134	
37	0.5	0.3	1	11.77	37	370	
38	0.5	0.5	2	11.77	37	464	
39	0.5	0	4	12	40	461	
40	0.5	0.5	4	12	40	1140	
41	1	0.2	3	11.97	39	710	[11]
42	1	0	3	11.93	40	630	
43	0.991	0.711	1	15.8	32	1774	[12]
44	3.004	0.762	1	15.8	32	1019	
45	2.489	0.762	1	15.8	32	1158	
46	1.492	0.762	1	15.8	32	1540	
47	3.016	0.889	1	15.8	32	1161	
48	0.059	0.029	5.95	15.7	34	58.5	[13]
49	0.059	0.058	5.95	15.7	34	70.91	
50	0.059	0.029	5.95	16.1	37	82.5	
51	0.059	0.058	5.95	16.1	37	98.93	
52	0.059	0.029	5.95	16.5	39.5	121.5	
53	0.059	0.058	5.95	16.5	39.5	142.9	
54	0.059	0.029	5.95	16.8	41.5	157.5	
55	0.059	0.058	5.95	16.8	41.5	184.9	
56	0.059	0.029	5.95	17.1	42.5	180.5	
57	0.059	0.058	5.95	17.1	42.5	211	
58	0.094	0.047	6	15.7	34	74.7	
59	0.094	0.094	6	15.7	34	91.5	
60	0.094	0.047	6	16.1	37	104.8	
61	0.094	0.094	6	16.1	37	127.5	
62	0.094	0.047	6	16.5	39.5	155.8	

(*continued*)

Table 1. (*continued*)

No Data	B (m)	D_f (m)	L/B	γ (kN/m^3)	ϕ (°)	q_u (kN/m^2)	Ref.
63	0.094	0.094	6	16.5	39.5	185.6	
64	0.094	0.047	6	16.8	41.5	206.8	
65	0.094	0.094	6	16.8	41.5	244.6	
66	0.094	0.047	6	17.1	42.5	235.6	
67	0.094	0.094	6	17.1	42.5	279.6	
68	0.152	0.075	5.95	15.7	34	98.2	
69	0.152	0.15	5.95	15.7	34	122.3	
70	0.152	0.075	5.95	16.1	37	143.3	
71	0.152	0.15	5.95	16.1	37	176.4	
72	0.152	0.075	5.95	16.5	39.5	211.2	
73	0.152	0.15	5.95	16.5	39.5	254.5	
74	0.152	0.075	5.95	16.8	41.5	285.3	
75	0.152	0.15	5.95	16.8	41.5	342.5	
76	0.152	0.075	5.95	17.1	42.5	335.3	
77	0.152	0.15	5.95	17.1	42.5	400.6	
78	0.094	0.047	1	15.7	34	67.7	
79	0.094	0.094	1	15.7	34	90.5	
80	0.094	0.047	1	16.1	37	98.8	
81	0.094	0.094	1	16.1	37	131.5	
82	0.094	0.047	1	16.5	39.5	147.8	
83	0.094	0.094	1	16.5	39.5	191.6	
84	0.094	0.047	1	16.8	41.5	196.8	
85	0.094	0.094	1	16.8	41.5	253.6	
86	0.094	0.047	1	17.1	42.5	228.8	
87	0.094	0.094	1	17.1	42.5	295.6	
88	0.152	0.075	1	15.7	34	91.2	
89	0.152	0.15	1	15.7	34	124.4	
90	0.152	0.075	1	16.1	37	135.2	
91	0.152	0.15	1	16.1	37	182.4	
92	0.152	0.075	1	16.5	39.5	201.2	
93	0.152	0.15	1	16.5	39.5	264.5	
94	0.152	0.075	1	16.8	41.5	276.3	

(*continued*)

Table 1. (*continued*)

No Data	B (m)	D_f (m)	L/B	γ (kN/m^3)	ϕ (°)	q_u (kN/m^2)	Ref.
95	0.152	0.15	1	16.8	41.5	361.5	
96	0.152	0.075	1	17.1	42.5	325.3	
97	0.152	0.15	1	17.1	42.5	423.6	

Table 2. Data testing.

No Data	B (m)	D_f (m)	L/B	γ_t (kN/m^3)	ϕ (°)	q_u (kN/m^2)	Ref.
1	0.08	0	1	17.2	42.8	133	[14]
2	0.15	0	1	17.2	42.8	246	
3	0.05	0	1	17.2	42.8	109	[15]
4	0.08	0	1	17.1	42.8	130	
5	0.1	0	1	17.1	42.8	152	
6	0.15	0	1	17.1	42.8	214	
7	0.2	0	1	17.1	42.8	266	
8	0.25	0	1	17.1	42.8	333	
9	0.3	0	1	17.1	42.8	404	

4 Result and Discussion

4.1 Development ANFIS Model

The Adaptive Neuro Fuzzy Inference System (ANFIS) is a hybrid of ANN and FIS in which membership functions and rules IF THEN are automatically determined from data input through a learning process. Figure 1 and Fig. 2 show the FL and ANN Architect models, respectively. The ANFIS toolbox MATLAB Student Version program provides multiple membership functions for inputs: trimf, trapmf, gbellmf, gaussmf, gauss2mf, pimf, dsigmf, and psigmf [7]. Figure 3, 4, 5, 6 and 7 demonstrate the gbellmf membership function of the FIS model for input data, which are width (B), depth (D_f), shape factor (L/B) of footing, unit weight of soil (γ) and friction angle (ϕ) of soil, and Fig. 8 shows the rule IF THEN.

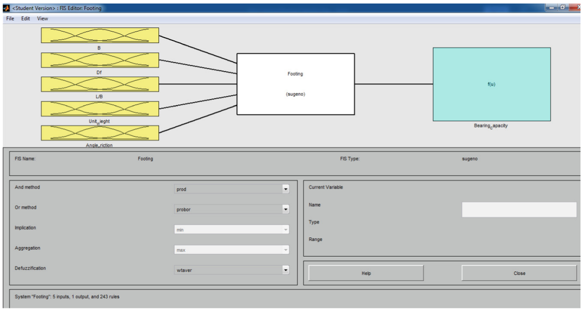

Fig. 1. FIS Model.

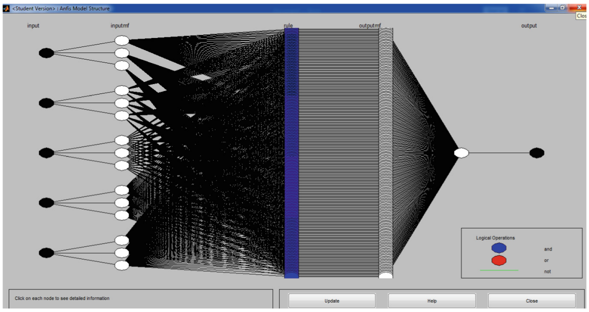

Fig. 2. ANN Architect model.

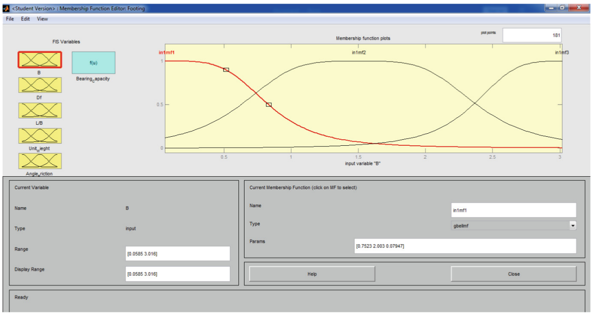

Fig. 3. Membership function width of footing (B).

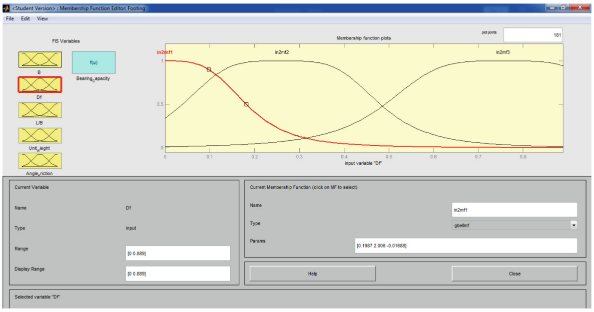

Fig. 4. Membership function depth of footing (D_f).

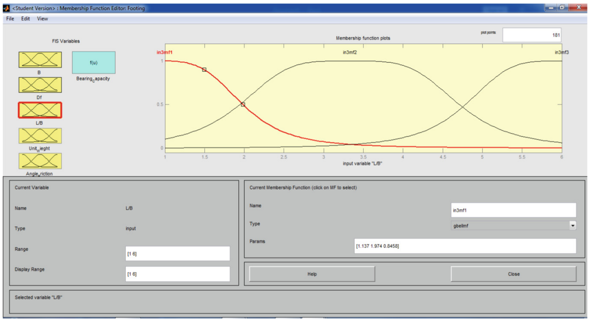

Fig. 5. Membership function shape factor of footing (L/B).

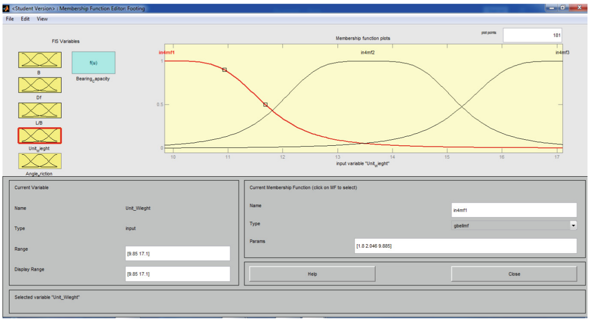

Fig. 6. Membership function unit weight of soil (γ).

4.2 Evaluation ANFIS Model

The results of the learning process were compared to the testing data to evaluate the performance of the constructed ANFIS model, as shown in Figs. 9 and 10. The correlation coefficient (R^2) for testing data was 0.98 with RMSE of 32.11 kN/m^2, indicating that the ANFIS model has a good level of accuracy.

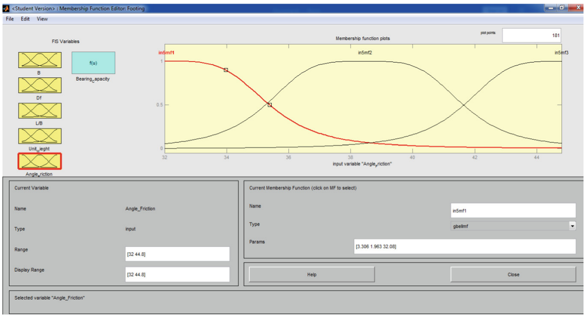

Fig. 7. Membership function friction angle of soil (ϕ).

Fig. 8. Rule IF THEN ANFIS model.

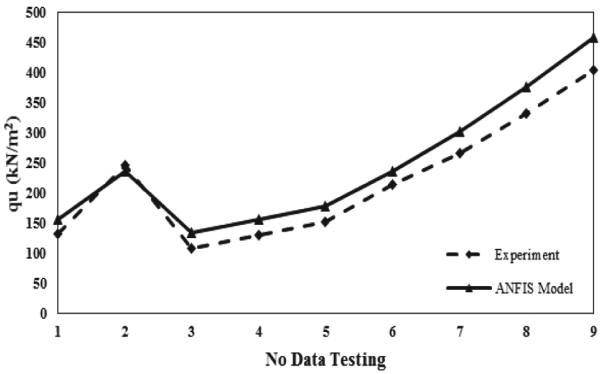

Fig. 9. Comparison of bearing capacity experiment and ANFIS model.

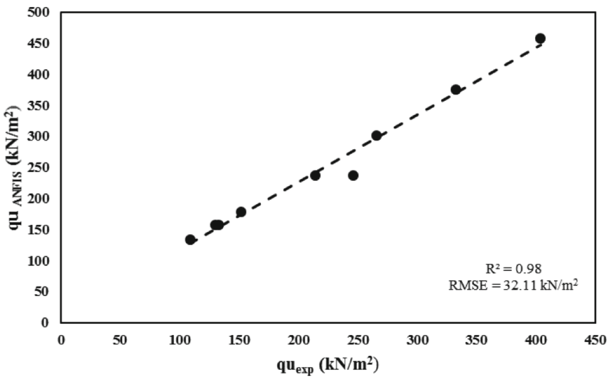

Fig. 10. Evaluation ANFIS model.

5 Conclusion

In this study, the ANFIS model was developed for predicting the ultimate bearing capacity of a footing on granular soil, where the parameter is important in the foundation design of a footing. The results of the analysis showed that the ANFIS model has a good level of accuracy compared with the experiment, where the correlation coefficient (R^2) for testing data was 0.98 with RMSE of 32.11 kN/m^2. This demonstrates that the ANFIS model developed is accurate in predicting the ultimate bearing capacity of footings on granular soil.

Acknowledgment. The Authors would like to thank financial support from the University of Mataram is gratefully acknowledged.

References

1. Terzaghi, K.: Theoretical soil mechanics. New York: John Wiley &Sons (1943).
2. Meyerhof, G. G.: Some recent research on the bearing capacity of foundations. Can Geotech J, 1(1), pp. 16–20 (1963).
3. Vesic AS.: Analysis of ultimate loads of shallow foundations. JSMFD, ASCE 99(1), pp. 45–73 (1973).
4. Makni, M., Daoud, A., Karray, M. A.: Application of Artificial Neural Network technique in Civil Engineering, Proceedings International Conference on Control, Engineering & Information Technology (CEIT'13), Vol. 2, 56–61 (2013).
5. Kalinli, A., Acar, M. C., Gündüz, Z.: New approaches to determine the ultimate bearing capacity of shallow foundations based on artificial neural networks and ant colony optimization, Engineering Geology (2010).
6. Jang, J.S.R.: ANFIS: Adaptive-Network-Based Fuzzy Inference System, IEEE Transactions on Systems, Man, And Cybernetics, Vol. 23, No. 3 (1993).
7. MATLAB, Neuro-Adaptive Learning, and ANFIS, https://www.mathworks.com/help/fuzzy/neuro-adaptive-learning-and-anfis.html.
8. Muhs, H., Elmiger, R., Weiß, K., Sohlreibung und Grenztragfähigkeit unter lotrecht und schräg belasteten Einzelfundamenten. Deutsche Forschungsgesellschaft für Bodenmechanik (DEGEBO), Berlin. HEFT 62 (1969).

9. Weiß, K.: Der Einfluß der Fundamentform auf die Grenztragfähigkeit flachgegründeter Fundamente. Deutsche Forschungsgesellschaft für Bodenmechanik (DEGEBO), Berlin. HEFT 65 (1970).
10. Muhs, H., Weiß, K.: Untersuchung von Grenztragfähigkeit und Setzungsverhalten flachgegründeter Einzelfundamente im ungleichförmigennichtbindigen Boden. Deutsche Forschungsgesellschaft für Bodenmechanik (DEGEBO), Berlin. HEFT 69 (1971).
11. Muhs, H., Weiß, K.: Inclined load tests on shallow strip footings. Proceedings of the 8th international conference on soil mechanism and foundation engineering, Vol. II, pp. 173–179 (1973).
12. Briaud, J.L., Gibbens, R.: Behaviour of five large spread footings in sand. Journal of Geotechnical and Geoenvironmental Engineering 125 (9), pp. 787–796 (1999).
13. Gandhi GN.: Study of bearing capacity factors developed from laboratory experiments on shallow footings on cohesionless soils. PhD thesis, Shri G.S, Institute of Tech and Science, Indore (MP) (2003).
14. Golder, H.Q.: The ultimate bearing pressure of rectangular footings. J. of the Institution of Civil Engineers 17, pp. 161–174 (1941).
15. Eastwood, W.: A comparison of the bearing power of footings on dry and inundated sand. Structural Engineering 29 (1), 332 (1951).
16. Padmini, D, Ilamparuthi, K., Sudheer, K. P.: Ultimate bearing capacity prediction of shallow foundations on cohesionless soils using neurofuzzy models. Computers and Geotechnics 35, pp. 33–46 (2008).