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Estimation of Oxygen Exchange during Treatment Sludge Composting through Multiple Regression and Artificial Neural Networks (Estimation of Oxygen Exchange during Composting)

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ABSTRACT: In general, amount of sludge will definitely increase in near future and composting processes, optimum composting conditions and compost use as fertilizer and soil amendment will then be significant research topics. The present study was conducted for O_2 parameter estimation by multiple regression and artificial neural networks methods. Daily temperature, CH_4, H_2S, CO_2 and O_2 measurements were performed over three different windrows during the composting period (136 days). Three different models were developed for each windrow. Multiple regression and artificial neural network methods were then applied to these models for O_2 estimations. High confidence levels were attained between the parameters of multiple regression analysis. However, correlation values in artificial neural network applications (R^2 = 0.65-0.98) were even higher. Thus, artificial neural network model applied for each windrow and model was highly confident. The present results indicated that temperature, CH_4, CO_2 and H_2S measurements performed during the composting of waste treatment sludge yielded satisfactory estimations for O_2. The recommended correlation may provide significant contributions to composting processes and implementations.

Key words: Waste sludge**,** Composting, Artificial neural networks, Correlation

INTRODUCTION

Sludge is an indispensable ultimate by product of entire traditional wastewater treatment processes (Bruce *et al* 1988). Composting of organic wastes including treatment sludge has been a common method applied for years. Compost is highly rich in nitrogen, phosphorus and potassium and usually used as secondary raw material fertilizer and soil amendment (Kranert *et al*. 2005). Domestic urban wastes may constitute an organic material source for soils (Banegas *et al*. 2007). Considering the carbon losses of the soils, such composted wastes of human-induced wastes can create a significant potential for soil transformation (Watteau and Villemin 2011).

Composting is a controlled biological process to speed up the biological decomposition of organic materials (Renkow and Rubin 1998). Fully composted material has several advantages such as providing a bio-fertilizer, relatively low air and water pollution, low operational cost and potential income source (Taiwo 2011). Compost treatments may enhance soil characteristics, isolate carbon dioxide indirectly and reduce greenhouse gas emissions directly (Brown *et al.* 2008).

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In general, amount of sludge will definitely increase in near future and composting processes, optimum composting conditions and compost use as fertilizer and soil amendment will then be significant research topics. Besides, widespread of composting will bring the issues of process control, compost quality and reliability and environmental impacts into agendas (Khalil *et al.* 2011).

Various bulking agents are used in composting to increase the volumes and improve the composting processes. Hay *et al*. (1988) used alternative bulking agents in sludge composting and composted sludge with hay or saw dust in a ratios respectively of 1:2 and 1:1 sludge:bulking agent (v:v) (Banegas *et al*. 2007). Molla *et al*. (2004) also used saw dust in sludge composting at a ratio of 1:1. Bousselhaj *et al*. (2004) investigated the potential of mixed composting of sludge with different bulking agents at 1:1 (w:w) ratio as nitrogenous fertilizer. Gouxue *et al*. (2001) composted waste sludge as to have C/N ratio of 30 by adding sufficient saw dust. Zubillaga and Lavado (2003) used sludge:saw dust mixture ratios of 1:2, 2:1 and 1:1 and investigated the stability indices of sludge composts. Eftoda and Mc Cartney (2004) used wood chips as bulking agents at ratios of 1:1, 1:2, 1:3 and 1:4. Chen *et al*. (2011) investigated H_2S mitigation through O_2 feedback control in large-scale sludge composting. Existing oxygen deficiency in windrow is the basic reason for H_2S formation. Reduced ventilation intervals or continuous air supply to meet high oxygen demand of windrows is an efficient way to cease H_2S formation during sludge composting. Khalil *et al*. (2011) investigated the effects of mixing intervals on physical, chemical and microbial parameters during the composting of domestic waste treatment sludge.

Artificial Neural Networks (ANNs) are employed sometimes to model the biochemical processes observed during the sludge composting through gathering simulated empirical data to be used in formulas of the analyses (Kim *et al*. 2011). Recently, artificial neural networks have been commonly used in geotechnical and other engineering practices (Sinha and Wang 2007; Gunaydin *et al*. 2010; Das and Basudhar 2008). ANNs are also used in water quality analyses (Soltani *et al*. 2010; Yao *et al*. 2011; Najah *et al*. 2012; Rankovic *et al*. 2012; Wen *et al*. 2013), nano-filtration practices (Al-Zoubi 2007), water distribution strategies (Jafar 2010), risk analyses (Pradhan and Lee 2009), phenol mineralization modeling in photo-fenton processes (André *et al*. 2014). Enayatollahi *et al*. (2014) compared the multiple regression analysis and artificial neural networks for rock fracture estimation in open-cast mines.

The objective of the present research is to investigate the possible use of artificial neural networks and multiple regression analysis to estimate O_2 values of compost windrows with different contents. Daily temperature, O_2, CO_2, CH_4 and H_2S measurements were taken for 24 weeks from 4 different compost windrows with different mixture rates. Multiple regression and artificial neural network models were applied to measurement data to find out the best reliable estimation method.

MATERIALS & METHODS

The sludge of domestic wastewater treatment facility of Sivas Province of Turkey was composted with leaves, branches, organic and inorganic wastes of aerated sand filter unit of the facility by using windrow composting technique. The windrow compositions and mixture rates are presented in Table 1.

Daily temperature and gas (CH_4, H_2S, CO_2, O_2) measurements were performed over the windrows (Table 2). Gas measurements were taken with a gas measurement probe (Hoeywell Neotronics Impact Pro) and temperature was measured with a temperature measurement device (Lutron TM-903A). Multiple regression and artificial neural network models were applied to resultant data.

The objective of multiple regression analysis is to define two or more independent variables simultaneously to explain the variations in a dependent variable. Temperature, CH_4, CO_2, and H_2S were recognized as independent variables and O_2 was recognized as a dependent variable. Multiple regression analysis was performed to determine the relationships of O_2 with four independent variables. Statistical analysis software "SPSS 11.0" was used for multiple regression analysis. The studied statistical variables are provided in Table 3 for each windrow. Three models were used in analysis. Temperature, CH_4, CO_2, H_2S were taken as the independent variables in Model I, CH_4, CO_2, H_2S in Model II, CO_2, H_2S in Model III and O_2 was taken as the dependent variable in all models.

Models were confirmed by taking F-test, t-test and correlation coefficients into consideration. Model statistical results are provided in Table 4. Significance of R^2 value can be assessed with t-test by assuming normal distribution and randomization of both variables. The test compares the t-value calculated by using the null hypothesis with the tabulated t-value. The confidence level was selected as 95% in this test. The null hypothesis is rejected when the calculated t-value is greater than the tabulated t-value. That indicates the significance of R. Otherwise, the null hypothesis in not rejected. That indicates this time the insignificance of R. As it can be seen from Table 4, t-values calculated for W1, W2 and W3 are greater than the tabulated t-values. In this case, R is significant. Results revealed that Model I yielded the best

Table 1. Mixture rates of windrows

	W1 (volume/m^3)	W2 (volume / m^3)	W3 (volume / m^3)
Waste sludge	0,75	1,0	0,5
Leaves	1,0	1,0	1,0
Branches	1,0	1,0	1,0
Organic trash coming out of the aerated sand trap unit	0,25	-	-
İnorganic trash coming out of the aerated sand trap unit	-	-	0,5
Soil	-	4,5	-

Table 2. Measurement results over the windrows

	W1					W2					W3				
	T C^0	CH_4 %V.	CO_2 %V.	H_2S ppm	O_2 %V.	T C^0	CH_4 %V.	CO_2 %V.	H_2S ppm	O_2 %V.	T C^0	CH_4 %V.	CO_2 %V.	H_2S ppm	O_2 %V.
1	21	0	2,4	0	17,3	6,4	0	0	0	20,9	25,3	0	2,4	0	2,6
2	22,3	1	2,4	48,4	1	8,7	0	2,4	0	18,9	27	0	2,4	0	4,2
3	23,7	0	2,4	0	8	8,8	0	0,1	0	18,2	30,7	0	2,4	0	6,3
4	27	0	2,4	0	7,3	9	0	0,9	0	20,4	30,7	0	2,4	0	15,5
5	28	0	2,4	0	15,7	9,2	0	0,9	0	18,4	31	2	2,4	60	0,2
6	29,6	0	2,4	0	15	10	0	2,4	0	17,5	31	0	2,4	0	1,3
7	30,1	1	2,4	17,5	0,4	10,4	0	0,5	0	19	31,6	0	2,4	60	0,3
8	30,4	0	2,4	0	13	10,4	0	1	0	19,3	32	0	2,1	21,5	1,4
9	30,5	2	2,4	60	0,3	10,5	0	2,4	0	18,9	33,1	1	1,7	60	0,2
10	30,5	0	2,4	0	15,1	10,6	0	2,4	0	18,4	33,7	0	2,4	0	4,1
11	30,5	0	2,4	0	7,5	10,8	0	2,4	0	18,5	33,8	0	2,4	0	5,6
12	30,6	0	2,4	0	8,8	11	0	2,4	0	18,4	34,6	0	2,4	0	3,4
13	31	0	2,4	0	0,8	11	0	1,8	0	18,1	34,7	0	2,4	0	13,6
14	31,1	0	2,4	49	1	11,1	0	2,4	0	17,3	34,9	0	2,4	0	0,7
15	31,3	2	1,7	60	0,2	11,2	0	2,4	0	18,5	35,2	0	2,4	0	10,3
16	32,1	0	2,4	0	12,5	11,2	0	1,7	0	17,5	35,4	0	2,4	19,1	0,4
17	33,5	0	2,4	0	17,3	11,3	0	1,4	0	19,5	35,8	0	2,4	0	5,6
18	34	0	2,4	4,8	0,8	11,5	0	1,7	0	18,9	35,9	0	2,4	0	0,8
19	34	0	2,4	0	16,9	11,5	0	2,4	0	18,9	36,6	0	2,4	0	10,8
20	34,4	0	2,4	0	12,8	11,6	0	0,6	0	20	36,7	0	2,4	22,9	0,3
21	34,4	0	2,4	0	8,8	12	0	1,4	0	18,9	37,2	3	2,4	60	4,3
22	34,5	0	2,4	0	11,9	12	0	2,4	0	17,1	37,5	0	2,4	0	0,6
23	34,7	0	2,4	0	11,4	12	0	2,4	0	17,1	37,7	0	2,4	0	9,2
24	35,5	0	2,4	0	17,9	12,1	0	0,4	0	20,1	37,8	0	2,4	0	2
25	36,6	0	2,4	16,6	0,6	12,2	0	2,4	0	18,4	37,9	0	2,4	0	12,6
26	36,8	0	2,4	0	12,1	12,4	0	1,3	0	18,6	39,2	0	2,4	0	3,2
27	37,5	0	2,4	0	11,4	12,4	0	2,4	0	17,7	39,4	0	2,4	0	1,2
28	37,5	0	2,4	0	12,8	12,4	0	2,4	0	17,8	40,1	0	2,4	0	1,4
29	37,8	0	2,4	0	15,2	12,4	0	2,4	0	17,6	40,2	0	2,4	0	1,1
30	38	0	2,4	0	16,6	12,5	0	1,6	0	18,8	40,3	1	2,4	55,3	0,5
31	38,5	0	2,4	0	6,4	12,7	0	2,4	0	18,5	40,8	0	2,4	0	4,8
32	38,7	0	2,4	10	0,9	12,8	0	2,4	0	18,7	40,9	1	2,4	3,7	1,7
33	38,7	1	2,4	9,9	1	12,9	0	2,4	0	17,9	41,2	0	2,4	0	15,5
34	38,7	0	2,4	0	14,5	12,9	0	2,4	0	16,7	41,2	0	2,4	0	10,4
35	38,7	0	2,4	0	12,4	13,4	0	1,8	0	17,4	41,3	0	2,4	0	4,1
36	39,5	0	2,4	0	17,4	13,5	0	2,4	0	15,9	41,4	1	2,4	3	1,5
37	39,5	0	2,4	0	14	13,6	0	2,4	0	17,8	41,5	0	2,4	0	15,8
38	39,5	0	2,4	0	14,4	13,6	0	2,4	0	16,1	41,5	0	2,4	0	1,8
39	39,7	0	2,4	60	0,5	13,8	0	2,4	0	17,1	41,8	0	2,4	0	12,3
40	39,7	0	2,4	0	15,3	13,9	0	2,4	0	17,4	42	0	2,3	60	0,5
41	40	0	2,4	0	7,7	14	0	2,4	0	18,1	42,2	0	2,4	60	0,2
42	40,2	0	2,4	0	10,9	14,1	0	1,1	0	19,9	42,3	0	2,4	0	2
43	40,4	0	2	28,4	0,5	14,2	0	1,4	0	18,9	42,5	0	2,4	60	0,3
44	40,5	0	2,3	0	10,4	14,3	0	2,4	0	19,5	42,5	0	2,4	0	0,8
45	40,5	0	2,4	0	10,9	14,3	0	1,6	0	19	42,7	0	2,4	0	0,8
46	40,7	0	2,4	0	10	14,5	0	2,4	0	18,3	42,7	0	2,4	0	6,4
47	40,8	0	2,4	0	16,2	14,5	0	2,4	0	15,7	42,7	0	2,4	0	1,3
48	40,9	0	2,4	60	0,5	14,6	0	2,4	0	17,9	43,1	0	2,4	0	3,5
49	41	0	2,4	0	11,1	14,7	0	1,5	0	18,6	43,3	0	2,4	0	2,9
50	41,1	0	2,4	0	16,9	14,7	0	2,4	0	16,9	44	0	2,4	0	1
51	41,1	0	2,4	0	15	14,7	0	1,9	0	16,9	44,3	2	1,6	60	0,2
52	41,1	0	2,4	0	16	14,9	0	2,4	0	17,3	44,3	0	2,4	0	8,6
53	41,2	0	2,4	0	14,3	15	0	2,4	0	18,6	44,3	0	2,4	0	2,2
54	41,2	0	2,4	0	15,5	15,4	0	1	0	20,4	44,3	0	2,4	0	2
55	41,3	0	2,4	0	12	15,6	0	2,4	0	17,8	44,4	0	0,3	0	18,9
56	41,5	0	2,4	0	13,8	15,6	0	2,4	0	17,6	44,4	0	2,4	0	13,1
57	41,7	0	2,4	0	13,9	15,6	0	1,4	0	19,7	44,5	0	2	40,6	0,4
58	41,8	0	2,4	0	9,4	15,8	0	1,4	0	16,5	44,5	0	2,4	60	0,4
59	41,9	0	2,4	0	12	16,5	0	2,4	0	14,8	44,6	0	2,4	0	1,1
60	42	1	2,4	60	2,5	16,5	0	2,4	0	17,9	44,7	1	2,3	60	1,7
61	42,4	0	2,4	0	13,8	17	0	2,4	0	16,1	44,7	0	2,4	60	0,5
62	42,4	0	2,4	0	19,5	17	0	2,4	0	14,8	44,9	0	2,4	0	3,8
63	42,4	0	2,4	0	9,4	17	0	2,4	0	15,3	45,2	0	2,4	0	1,2
64	42,5	0	2,4	0	14,4	17	0	2,4	0	15,9	45,3	4	2,4	60	0,8
65	42,7	0	1,7	0	11	17,2	0	2,4	0	16,7	45,5	0	2,4	0	1,1
66	43	0	2,4	0	17,9	17,6	0	2,4	0	16,9	45,6	0	2,4	3,5	0,7
67	43,1	1	1,8	19,1	1	17,8	0	2,4	0	1,2	45,6	0	2,4	0	2,6

Table 2 .(Continued). Measurement results over the windrows

	W1					W2					W3				
	T C^0	CH_4 %V.	CO_2 %V.	H_2S ppm	O_2 %V.	T C^0	CH_4 %V.	CO_2 %V.	H_2S ppm	O_2 %V.	T C^0	CH_4 %V.	CO_2 %V.	H_2S ppm	O_2 %V.
68	43,3	0	2,4	0	10,9	18,1	0	2,4	0	17	46,4	0	2,4	0	2,6
69	43,5	0	2,4	7,4	4	18,2	0	2,4	0	17	46,5	0	2,4	0	4
70	43,5	0	2,4	0	8,7	18,3	0	0	0	20,4	46,6	0	2,4	0	12,4
71	43,5	0	2,4	0	12,6	18,3	0	2	0	17,3	46,6	0	2,4	0	3,8
72	43,7	0	2,4	0	8,4	18,3	0	2,4	0	16,9	46,6	0	2,4	60	0,3
73	43,7	0	2,4	0	14,5	18,3	0	2,4	0	16,8	46,8	0	2,4	0	11,3
74	43,7	0	2,4	0	15,6	18,5	0	2,4	0	16	46,8	0	2,4	0	2,9
75	43,7	0	2,4	0	12,3	18,7	0	2,4	0	17,3	46,8	0	1,3	0	11,3
76	44	1	2,4	3,5	1,5	19	0	2,4	0	14,9	46,9	0	0,7	0	19,6
77	44,5	0	2,4	0	8,4	19,2	0	2,4	0	16,3	47	0	2,4	0	0,7
78	44,5	0	1,4	0	18,8	19,3	0	2,4	0	16	47,3	0	2,4	0	0,5
79	44,7	0	2,4	0	7,5	19,4	0	2,4	0	16,4	47,3	0	2,4	0	2,4
80	44,7	0	2,4	0	13,8	19,5	0	2,4	0	16,5	47,4	0	2,4	9,6	0,9
81	44,9	0	2,4	0	8,4	19,5	0	2,4	0	17	47,4	0	2,4	0	2,3
82	45	0	2,4	0	16,7	19,5	0	2,4	0	16,1	47,5	3	2,4	19,5	1
83	45	0	2,4	0	17,7	19,7	0	2,4	0	17,7	47,5	0	2,4	16,5	0,4
84	45,2	2	2,4	7,9	0,8	20,2	0	2,4	0	15	47,8	0	2,4	0	0,6
85	45,2	0	2,4	0	8	20,7	0	1,5	2	0,2	47,8	0	2,4	60	0,5
86	45,2	0	2,4	0	14,1	20,9	0	1,2	16,8	0,3	48,1	2	2,4	10	0,5
87	45,4	0	2,4	0	17,6	21,4	0	2,4	0	17,8	48,2	0	2,4	0	11,1
88	45,7	1	2,4	60	2,4	22,2	0	2,4	0	12,9	48,3	1	2	0	13,4
89	45,8	0	2,4	0	12,3	22,4	0	2,1	5,6	0,3	48,4	0	2,4	0	14,9
90	46	1	2,4	25	0,5	23,5	0	2,4	0	17,2	48,4	0	2,4	0	2,7
91	46	2	2,4	5,4	1	23,8	0	2,4	0	17,2	48,9	0	2,4	0	1,2
92	46,1	0	2,4	0	13,1	25,2	0	2,4	0	14,2	49	0	2,4	0	15,3
93	46,2	0	2,1	0	16,5	25,2	0	2,4	0	16,2	49,3	1	1,8	3,2	1,3
94	46,6	0	2,4	0	15,5	25,3	0	2,4	0	18,1	49,4	0	2,4	0	5,9
95	46,6	0	2,4	0	13,1	25,5	0	2,4	0	16,6	49,4	0	2,4	0	1,5
96	47	2	2,4	60	0,5	25,7	0	2,4	0	15,6	49,5	0	2,4	0	8
97	47	0	2,4	0	9,9	26,1	0	1,4	9,9	1,6	49,5	0	2,4	0	4,2
98	47,5	0	2	0	17,1	26,7	0	1,7	0	16,6	49,7	0	2,4	0	3
99	47,5	0	0,6	0	19	27	0	2,4	0	16	49,8	0	2,4	0	7,8
100	47,7	0	2,4	0	14,2	27,2	0	2,4	6,5	0,4	50	0	2,4	0	1,1
101	47,7	0	2,4	0	13,2	30,6	0	2,4	0	6	50,3	0	2,4	0	13,8
102	47,8	0	2,3	0	15,3	30,6	0	2,4	0	2,2	51,1	4	1,4	60	0,2
103	47,9	0	2,4	0	13,5	32,5	0	2,4	0	5,1	51,8	0	2,4	0	4,9
104	48	0	2,4	0	18,6	32,8	1	2,4	9,7	4	52	2	2,4	30,7	0,4
105	48,1	0	2,4	0	17,2	33,3	0	2,4	0	12,3	52,2	0	2,4	0	1,8
106	48,5	0	2,4	0	15,5	33,8	2	1,6	11,3	0,4	52,5	1	2,4	2,2	6,3
107	49,3	0	2,4	0	13,1	33,9	0	2,4	0	10,4	52,5	0	2,4	0	1,4
108	49,6	0	2,4	0	16,7	34,6	0	2,4	15,5	0,5	52,6	0	2,4	0	2,1
109	49,6	0	2,4	0	10,7	34,6	0	2,3	0	4,5	52,7	1	2,4	0	5,2
110	50,1	0	2,4	0	15,8	34,9	0	2,4	3,6	0,6	52,7	0	2,4	0	4,1
111	50,8	0	2,4	0	10,5	35	2	2,4	60	0,4	52,8	3	2,4	60	0,4
112	50,8	0	2,3	0	16,3	35,7	2	2,4	60	1	53,2	1	2,4	16,8	0,6
113	51,9	0	2,4	0	15,4	35,7	0	2,4	59,1	0,7	53,3	1	1,4	0	9,8
114	52,2	0	1,3	0	12,8	36,2	1	1,7	14,5	0,4	53,3	0	2,4	0	12,1
115	52,2	0	2,4	0	11,5	36,6	0	2,4	0	4	53,5	1	2,4	5	0,5
116	53,6	0	2,4	0	16,7	36,7	0	2,1	0	10,1	53,5	0	2,4	0	13,3
117	54,3	0	1,9	0	18,8	36,9	0	2,4	0	0,6	54	4	1,6	60	0,2
118	54,5	0	2,4	0	16,3	36,9	0	2,4	0	5,5	54,3	0	2,4	0	11,2
119	54,7	0	2,4	2,1	3,4	37,4	0	2,4	0	4,8	54,4	0	2,4	0	9,8
120	54,7	0	2,4	0	14,1	37,5	0	1,6	0	3,2	55,5	5	2,4	60	0,3
121	54,7	0	2,4	4,2	6,7	38,5	0	2,4	0	6,1	55,5	0	0,7	0	19,7
122	55,6	0	2,4	0	10,2	38,6	1	2,4	3	0,6	55,6	1	2,2	60	0,6
123	56	0	2,4	0	9,4	38,7	2	2,4	6,6	0,6	55,7	0	2,1	2,4	15,7
124	56,1	0	2,4	0	5	39,2	2	2,4	17,6	0,4	56,1	0	2,4	0	15,8
125	56,1	0	2,4	0	7,3	39,8	2	2,4	19,7	0,8	56,2	0	2,4	0	9,7
126	56,5	0	2,4	0	17	39,8	0	2,4	0	1,9	56,6	2	2,4	5	0,7
127	57,4	5	2,4	60	0,5	40	2	2,4	60	0,5	57,7	0	2,4	0	14,3
128	57,9	1	2,4	10,6	4,9	40,3	1	2,4	35,2	0,3	59,3	1	1,5	0	5,6
129	58,3	0	2,4	0	8	40,4	2	2,4	60	0,5	59,9	0	0,6	0	20,5
130	60	0	0,3	0	19,9	40,7	0	2,4	20	0,4	61,1	0	2,4	0	8,3
131	61,8	0	2,4	0	7,3	41,6	0	2,4	55,6	0,3	62,9	0	2,4	0	12,6
132	62,5	0	2,1	0	17,4	41,7	0	2,4	37,5	0,5	65,8	0	2,4	2,2	8,7
133	62,8	0	2,4	0	4,8	43,9	1	2,4	13,8	4,3	66,5	0	2,4	0	10,8
134	65,5	0	2,4	7	11,2	44,3	2	2,2	12,9	0,9	66,7	0	2,4	0	5,2
135	70	1	1,7	60	1,6	48,5	1	2,4	32,7	0,4	67,5	0	2,4	0	12,2
136	70,6	0	2,4	2,1	4,2	51,2	0	2,4	0	0,8	68,2	1	2,4	2,6	1,9

Table 3. Statistics of the variables studied

	W1					W2					W3				
	Temperature (ºC)	CH_4 (%V)	CO_2 (%V)	H_2S (ppm)	Oxygen (%V)	Temperature (ºC)	CH_4 (%V)	CO_2 (%V)	H_2S (ppm)	Oxygen (%V)	Temperature (ºC)	CH_4 (%V)	CO_2 (%V)	H_2S (ppm)	Oxygen (%V)
Mean	43,67794	0,183824	2,319853	6,021324	10,80809	21,73529	0,176471	2,113235	4,772794	12,86838	46,04485	0,375	2,282353	10,55368	5,152206
Maximum	70,6	5	2,4	60	19,9	51,2	2	2,4	60	20,9	68,2	5	2,4	60	20,5
Minimum	21	0	0,3	0	0,2	6,4	0	0	0	0,2	25,3	0	0,3	0	0,2
Median	43,4	0	2,4	0	12,2	18,15	0	2,4	0	16,75	46,45	0	2,4	0	2,6
Variatian	81,67981	0,373366	0,085899	260,4321	32,75082	116,4279	0,279739	0,316564	179,6377	53,82129	69,80338	0,858333	0,135242	455,5333	29,52059
Standard Deviation	9,037688	0,611037	0,293086	16,13791	5,722833	10,79018	0,528903	0,56264	13,4029	7,336299	8,354842	0,926463	0,367752	21,34323	5,433285
Skewness	0,309208	4,822993	-4,81395	2,809252	-0,56606	0,812557	2,909508	-2,09312	3,288404	-0,87281	0,20817	2,982447	-3,64122	1,786172	1,064189
Kurtosis	0,626976	30,09719	26,07652	6,480513	-0,84278	-0,59424	7,065112	3,845255	10,23989	-1,02281	0,318955	9,097313	13,50817	1,40444	-0,03189

estimations for W2. There was a medium level significant relationship (R^2=0.46-0.32) ($p<0.05$) in other models. Analysis of variance was used to test the significance of regression. The confidence level was selected as 95% in this test. The null hypothesis is rejected when the calculated F-value is greater than the tabulated F-value. That indicates a real relationship between dependent and independent variables. As seen in Tables, calculated F-values are greater than the tabulated F-values in all models. Therefore, it was concluded that the models were valid.

During the last decade, researchers investigating complex engineering problems started to use ANNs to solve engineering problems. Artificial neural networks are simplified models of biological structure of human brain. These models are organized in layers and composed of interconnected simple processing units and neurons. Large connections among the neurons allow them to gain a learning capacity for estimated data. A simple ANN architecture is presented in Fig. 1 where inputs are indicated by x_1, x_2, …x_n and weight coefficients of each input are indicated by W_{k1}, W_{k2}, …W_{kn}. Thus, x_n represents input signals and W_{kn} represents weight coefficients of these signals. The core gives the weighted sum of entire input signals. The results from the thresholding function of the network are indicated by Y.

Back-propagation algorithm is a training algorithm and commonly used in various disciplines, especially in engineering applications. This method is commonly used because of high training capacity and simple algorithm. There are three layers of back-propagation network algorithm model as of input, hidden and output (Fig. 2). It is possible to increase the number of hidden layers in ANN based on the nature of the problem. Computer-aided software MATLAB was used for ANN calculations (Demuth and Beale 2001).

In this study, 4 input variables and 3 different models were used. The 4 input variables used in Model I were Temperature, CH_4, CO_2, H_2S and output variable was O_2.

Statistical performance of the models was assessed by using the statistical parameters of mean (μ), standard error (SE), standard deviation (σ) and regression coefficient (R^2). Statistical performance of W1 is provided in Table 5, W2 in Table 6 and W3 in Table 7.

With regard to R^2 and SE terms (Table 5), all three models seemed to be good models. For W2 (Table 6) R^2 values respectively of 0.98, 0.92, 0.96 for each model were quite good. With regard to R^2 values of W3 (Table 7), the values were lower than the values for W1 and W2, but they were still highly significant. While W2 data yielded quite better outcomes than the other

Table 4. Statistical result of the selected multiple regression model.

Model	İndependent Value	Dependent Value	R^2	Adjusted R^2	Unstandardized Coefficients	Standard Error	Calculated F value	Tabulated F value	Sign.	Calculated t	Tabulated t value	Sig.
I	T	O_2	0,46	0,44	0,00039	0,04204	27,44	2,37	0,00000	0,00930	±1,67	0,99259
	CH_4				-1,7792	0,78929				-2,25416		0,02585
	CO_2				-3,47525	1,29009				-2,69379		0,00799
	H_2S				-0,18593	0,02998				-6,20194		0,00084
II	CH_4	O_2	0,46	0,44	-1,77839	0,78141	36,88	2,37	0,00000	-2,27586	±1,67	0,02447
	CO_2				-3,47778	1,25634				-2,76819		0,00645
	H_2S				-0,18597	0,02964				-6,27498		0,00057
III	CO_2	O_2	0,44	0,43	-3,52391	1,27576	51,12	2,37	0,00000	-2,76221	±1,67	0,00656
	H_2S				-0,22902	0,02317				-9,88459		0,00000

T:Temperature;

(W1)

Model	İndependent Value	Dependent Value	R^2	Adjusted R^2	Unstandardized Coefficients	Standard Error	Calculated F value	Tabulated F value	Sign.	Calculated t	Tabulated t value	Sig.
I	T	O_2	0,78	0,77	-0,52455	0,03649	115,17693	2,37	0,00000	-14,37127	±1,67	0,00000
	CH_4				-0,57147	0,77556				-0,73685		0,46253
	CO_2				0,32775	0,56672				0,57833		0,56404
	H_2S				-0,08399	0,03076				-2,73071		0,00719
II	CH_4	O_2	0,43	0,42	-3,87003	1,18464	33,13354	2,37	0,00000	-3,26685	±1,67	0,00139
	CO_2				-2,10984	0,86469				-2,43999		0,01602
	H_2S				-0,21762	0,04688				-4,64172		0,02040
III	CO_2	O_2	0,38	0,37	-2,19166	0,89521	41,35604	2,37	0,00000	-2,44821	±1,67	0,01566
	H_2S				-0,31461	0,03758				-8,37171		0,00001

(W2)

Model	İndependent Value	Dependent Value	R^2	Adjusted R^2	Unstandardized Coefficients	Standard Error	Calculated F value	Tabulated F value	Sign.	Calculated t	Tabulated t value	Sig.
I	T	O_2	0,37	0,35	0,10489	0,04724	18,90399	2,37	0,00000	2,22080	±1,67	0,02808
	CH_4				-0,97954	0,51096				-1,91706		0,05714
	CO_2				-5,87695	1,04822				-5,60661		0,00107
	H_2S				-0,08417	0,02194				-3,83599		0,00019
II	CH_4	O_2	0,34	0,33	-0,72297	0,50509	22,87979	2,37	0,00000	-1,43138	±1,67	0,15469
	CO_2				-6,18547	1,05433				-5,86673		0,00114
	H_2S				-0,0946	0,02175				-4,34943		0,01825
III	CO_2	O_2	0,33	0,32	-5,99509	1,05002	33,03476	2,37	0,00000	-5,70948	±1,67	0,00236
	H_2S				-0,11203	0,01809				-6,19238		0,00085

(W3)

windrows, Model II of this Table also had better performance than the other ANN models. Experimental O_2 values and comparison of model results are presented in Fig.s 3, 4 and 6. Smith (1986) indicated a significant relationship between measured and calculated values when the R value of a model is greater than 0.80. The R^2 values obtained in Tables 5, 6 and 7 were also obtained in calculations respectively in Fig.s 3, 4 and 6. All these results indicate a significant relationship between the values observed in models created for each three windrows. Training, validation and test data of the best estimator ANNs model are additionally presented in Fig. 5.

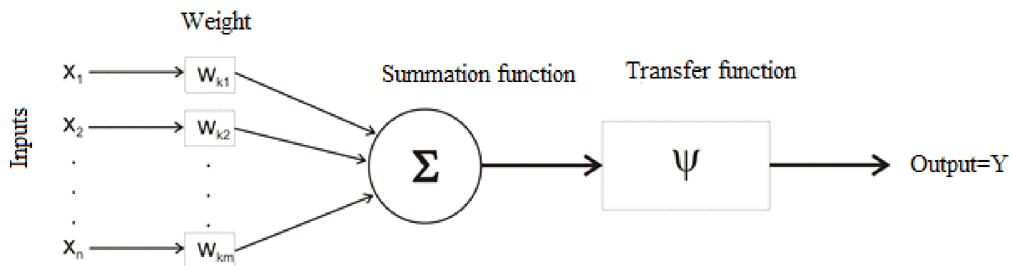

Fig. 1. Artificial Neural Network (ANN) cell pattern

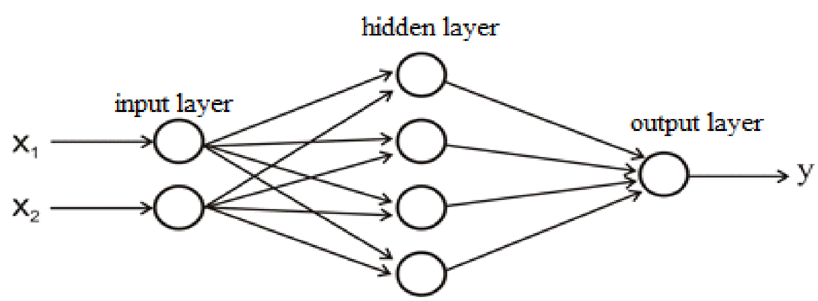

Fig. 2. Simple architecture of back-propagation algorithm of ANN

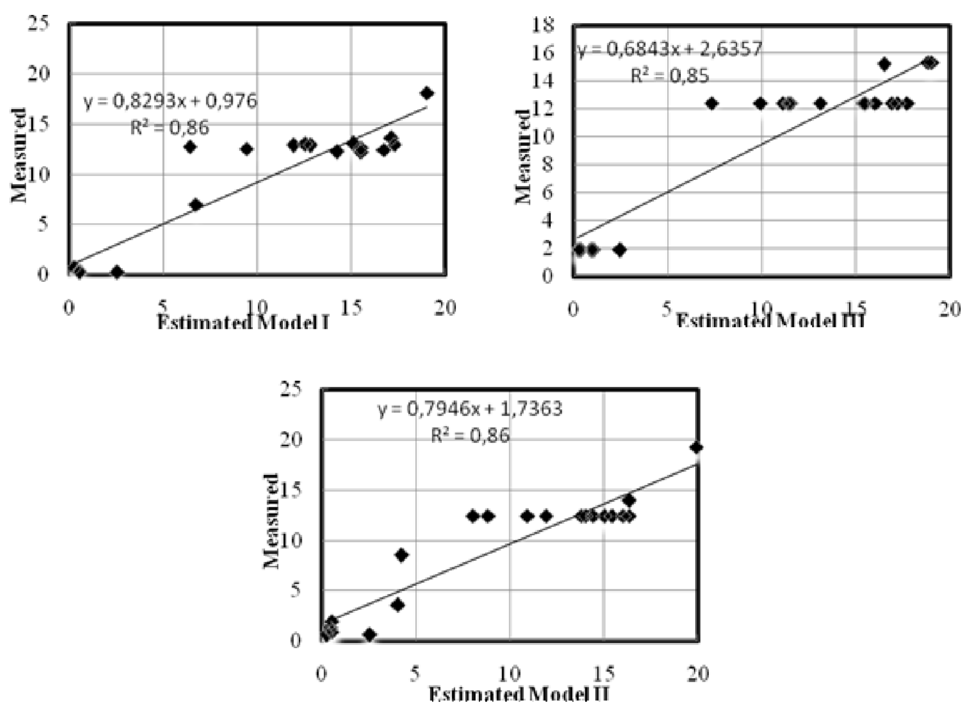

Fig. 3. Comparison between the predicted by W1 and observed values of oxygen.

Table 5. Statistical performance of the ANNs models (W1)

Model	Inputs	Structure	R^2	STD	SE	µ
I	Temperature, CH_4, CO_2, H_2S	4-3-1	0,86	6,103	2,603	1,483
II	CH_4, CO_2, H_2S	3-3-1	0,86	5,618	2,501	1,021
III	CO_2, H_2S	2-1-1	0,85	5,011	2,698	0,957

STD: Standard deviation; SE: Standard error; µ: Mean

Table 6. Statistical performance of the ANNs models (W2)

Model	Inputs	Structure	R^2	STD	SE	µ
I	Temperature, CH_4, CO_2, H_2S	4-3-1	0,98	7,171	1,129	0,335
II	CH_4, CO_2, H_2S	3-4-1	0,92	5,367	1,772	1,078
III	CO_2, H_2S	2-1-1	0,96	7,393	1,638	1,265

STD: Standard deviation; SE: Standard error; µ: Mean

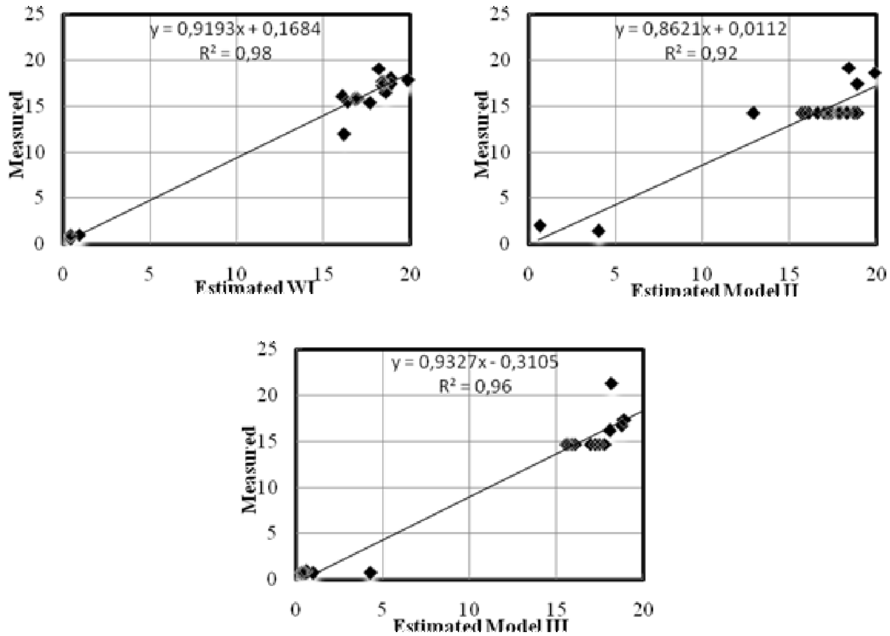

Fig. 4. Comparison between the predicted by W2 and observed values of oxygen.

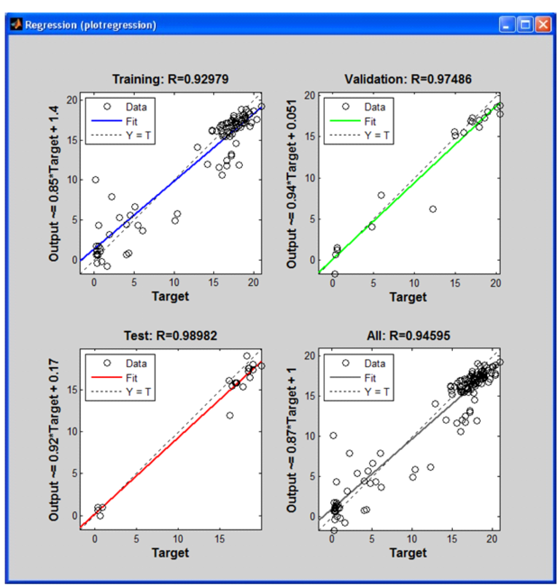

Fig. 5. The training, validation and testing data of Model I.

Table 7. Statistical performance of the ANNs models (W3)

Model	Inputs	Structure	R^2	STD	SE	µ
I	Temperature, CH_4, CO_2, H_2S	4-3-1	0,68	5,472	3,484	0,622
II	CH_4, CO_2, H_2S	3-4-1	0,65	3,997	3,246	1,858
III	CO_2, H_2S	2-1-1	0,75	4,389	2,203	0,471

STD: Standard deviation; SE: Standard error; µ: Mean

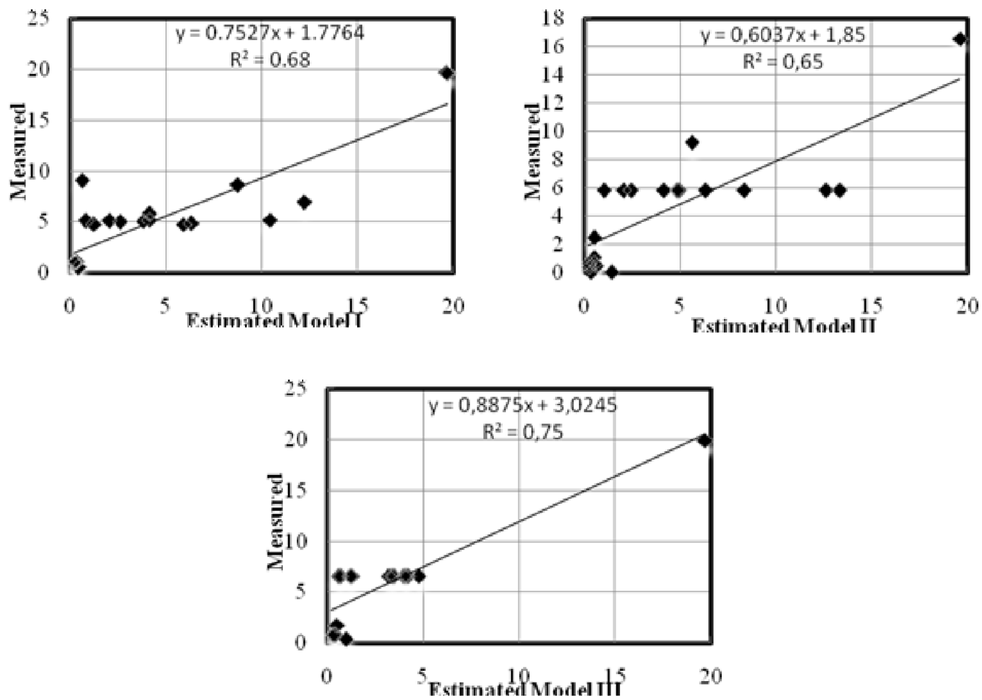

Fig.6. Comparison between the predicted by W3 and observed values of oxygen.

CONCLUSIONS

The present research was conducted to estimate variations in O_2 levels of compost windrows with different characteristics based on temperature CH_4, CO_2 and H_2S by using MRA and ANN models. ANN models yielded higher correlation coefficients (R^2) for each model created for different windrows. While R^2 values of W1 in ANN for each model were respectively observed as 0.86, 0.86, 0.85, the values in MRA were respectively observed as 0.46, 0.46, 0.44. For W2, the values were 0.98, 0.92, 0.96 in ANN and 0.78, 0.43, 0.38 in MRA. For W3, the values were 0.68, 0.65, 0.75 in ANN and 0.37, 0.34, 0.33 in MRA. In MRA, higher calculated F-values than the tabulated F-values indicate higher reliability of the method. Three different ANN models were created in three different compost windrows by using 136 test data to estimate oxygen levels. The best result was obtained in W2 windrow from the Model I (R^2=0.98). There were also significant relationships between measured and calculated values of the other models.

With this study, multiple regression and artificial neural network models were applied to temperature, CH_4, CO_2 and H_2S measurements from different compost windrows to estimate the O_2 levels of windrows. ANN applied for each windrow and model had quite high reliability. These findings indicated that temperature, CH_4, CO_2 and H_2S measurements during the composting process could be used to estimate O_2 values which is the most significant parameter in composting operations. The present study is the first study investigating possible use of ANN and MRA to estimate variations in O_2 levels based on temperature and other gases formed during the composting processes.

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