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Trip attraction model using radial basis function neural networks

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Abstract

Trip Attraction model with seven independent variables, i.e., population size, number of schools, number of students, number of teachers, areas of school buildings, number of offices, and number of houses applying Radial Basis Function Neural Networks (RBFNN) is presented in this paper. The data used in this study were derived from the origin destination survey in Palembang and the model was developed using 85 sets of land use - trip attraction data. A comparison was made between RBF model and regression model. The results show that RBF model performs better than regression model in predicting trip attraction and important variables are number of students, number of teachers, total areas of school buildings and number of offices.

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Keywords:Trip Attraction, Prediction, Radial Basis Function Neural Networks

1. Introduction

In city transportation modeling, trip attraction model is very important to predict the attraction of the trip in the future, which in turn is used to plan the need for city transportation facilities and infrastructures.

The trip attraction modeling in a city can be implemented by connecting the trip attraction derived from the origin destination survey result and land use parameters in each determined zone. In Palembang the origin-destination matrix has been used in urban transportation model for the development of urban transportation facilities and infrastructures [1, 2]. An improved accuracy of trip generating model is essential to get a better result of trip predictions.

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The model development of trip generation and trip attraction in Indonesia has been widely reported, particularly using regression models [3, 4, 5, 6, 7, 8]. The trip generation model using Artificial Neural Network (ANN) with Back Propagation Learning Algorithm has also been reported [9].

This paper discusses the RBFNN application in modeling trip attraction in Palembang, given the shortage of ANN models which take a long time to achieving convergent condition and can be trapped in minimum local condition in selecting the optimal criteria during learning procedure of the network [10]. Contrary to ANN, the RBFNN requires swift time to reach the convergent condition and ensures global convergent conditions. The RBFNN model has also been successful in the field of engineering applications [11, 12, 13, 14, 15].

The aims of the study are: (1) modeling the trip attraction in Palembang by using the Radial Basis Function Neural Network, and (2) comparing the RBFNN modeling results with the regression analysis model.

2. Methodology

In this study the trip attraction model in Palembang was developed using the origin destination matrix and data of land use in Palembang in 2009 and the model was developed using RBFNN and regression analysis. The data used are shown in Appendix A. The results of the attraction model with RBFNN were then compared with the results of the regression analysis model. The methodology and parts of RBFNN models, variables and analysis used are described in the following discussion.

2.1. Radial Basis Function Neural Networks

2.1.1. The topology of RBFNN

A RBFNN is a feedforward neural network that consists of three layers: input layer, hidden layer and output layer. Fig. 1 shows a typical architecture of a RBFNN. In the topology of networks, a RBFNN is similar to a special case of multilayer feedforward neural networks, but different in terms of node characteristics and learning algorithm.

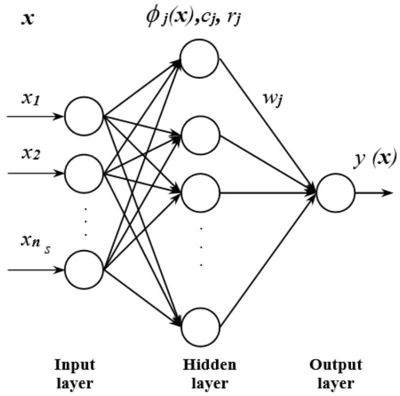

Fig. 1. Radial Basis Function Neural Networks

There is no calculation in input layer nodes. The input layer nodes only pass the input data to the hidden layer. The input layer consist of n_s nodes where input vector $x = (x_1, x_2,..., x_{ns})$. The hidden layer consists of n nodes and each hidden node $j = 1,2,..., n$ has a center value c_j. Each hidden layer node performs a nonlinear transformation of the input data onto new space through the radial basis function. The most common choice for the radial basis function is a Gaussian function, given by:

$$\phi_j(\boldsymbol{x}) = \exp\left(-\left\| \boldsymbol{x} - c_j \right\|^2 / r_j^2\right) \tag{1}$$

where $\| \boldsymbol{x} - c_j \|$ represents the Euclidean distance between input vector ($\boldsymbol{x}$) and the radial basis function center (c_j). r_j is the width of radial basis function.

The output layer operation is linear, given by

$$y(\boldsymbol{x}) = \sum_{j=1}^{n} w_j . \phi_j(\boldsymbol{x}) \qquad (2)$$

where w_j are the connection weight of hidden layer to output layer and n is number of hidden node.

Since the RBFNN output is a simple linear combination, the parameter solution can be obtained using linear optimization methods. Therefore, it has fast convergence time and is guaranteed to converge to global optimum parameter. Moody et al. [16] demonstrated that the radial basis function networks learn faster than multilayer perceptron network. Park et al. [17] proved theoretically that radial basis function network are capable of universal approximation and learning without local minima, therefore it is guaranteed to converge to global optimum parameter.

Training of RBFNN involves determination of the following parameters.

- Number of hidden layer nodes.
- The center and the width of each radial basis function in each node.
- The connection weight of hidden layer to output layer.

2.1.2. Training Methodology

The orthogonal least squares (OLS) learning algorithm [10] is usually used to determine the center and the optimum number of hidden nodes. The OLS algorithm is operating in a forward selection manner. The procedure chooses the radial basis function center one by one in a rational way until an adequate network has been constructed. Once the optimum numbers of the hidden nodes and their centers are found, the connection weights can be determined.

2.2. Variables and Analysis

The dependent variable in this research is trip attraction defined as the number of vehicles (cars, motorcycles, bicycles) entering a region observed during morning rush hours. Observations were made in 85 kelurahan in Palembang. Seven independent variables used as predictors were:

- number of residents registered in the kelurahan (x_1)
- number of schools and universities in the kelurahan (x_2)
- number of students registered in schools or universities in the kelurahan (x_3)
- number of teachers teaching at the schools or universities in the kelurahan (x_4)
- number of offices in the kelurahan (x_5)
- total areas of school and university buildings in the kelurahan (x_6)
- number of houses in the kelurahan (x_7)

Data were collected from local central bureau of statistics. Table 1 displays descriptive statistics of all variables used in this research.

Table 1. Descriptive statistics

	N	Minimum	Maximum	Mean	Std. Deviation
residents	85	2228	46031	14664.72	7508.579
schools	85	1	19	5.87	4.056
students	85	300	28890	3213.98	3709.886
teachers	85	12	1709	219.07	255.812
school areas	85	70	82961	10666.18	15811.643
offices	85	1	26	3.00	4.006
houses	85	12	7391	2587.75	1648.396
trip	85	35	9400	1315.66	1336.249
Valid N (listwise)	85				

In analysis, comparison between ordinary regression and radial basis function (RBF) models were made using the SPSS statistical package. Stepwise procedure was used to develop regression model based on ordinary least squares approach. Data were standardized using the following equation:

$$Z = \frac{X-\mu}{\sigma} \tag{3}$$

where X is observed value, μ is the mean, and σ is the standard deviation. This standardization process yields variable Z with zero meand and unit variance.

3. Results and Discussion

Regression analysis gives coefficients of all seven predictors as given in Table 2. The most significant predictors (p<0.10) are number of students (x_3), teachers (x_4), and offices (x_5), and total areas of schools (x_6). It is clear why stepwise procedure gives the following equation:

$$Y = 629.18 + 0.522X_3 - 4.518X_4 \tag{4}$$

with $R^2 = 0{,}414$ ($F = 28.98, p = 0.000$). This means number of students and number of teachers alone can explain 41.4% of variation in trip attraction. Inclusion of X_5 (number of offices) in the model increases R^2 only by 0.02. Notice that regressing trip attraction over all seven predictors gives $R^2 = 0.459$, which means the other five predictors contribute less than 5% in the model.

Table 2 Coefficients of predictors in regression analysis

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	427.576	269.849		1.584	.117
	residents	-.001	.027	-.008	-.052	.959
	schools	5.702	42.026	.017	.136	.892
	students	.500	.138	1.389	3.627	.001
	teachers	-3.679	1.998	-.704	-1.841	.069
	school areas	-.018	.010	-.215	-1.857	.067
	offices	57.438	29.414	.172	1.953	.054
	houses	.037	.107	.046	.346	.730

Dependent Variable: trip

For radial basis function (RBF) analysis, 50 cases (58.8%) were assigned to the training sample, 24 cases (28.2%) to the testing sample, and 11 cases (12.9%) to holdout sample. Network information is given in Table 3

Table 3. RBF network information

Input Layer	Covariates	1	residents
		2	schools
		3	students
		4	teachers
		5	school areas
		6	offices
		7	houses
	Number of Units		7
	Rescaling Method for Covariates		Standardized
Hidden Layer	Number of Units		5a
	Activation Function		Softmax
Output Layer	Dependent Variables	1	trip
	Number of Units		1
	Rescaling Method for Scale Dependents		Standardized
	Activation Function		Identity
	Error Function		Sum of Squares

a. Determined by the testing data criterion: The "best" number of hidden units is the one that yields the smallest error in the testing data.

Table 4. RBF parameter estimates

		Predicted					
		Hidden Layer[a]					Output Layer
Predictor		H(1)	H(2)	H(3)	H(4)	H(5)	y
Input Layer	x1	4.048	-.529	.863	.296	.176	
	x2	3.393	-.354	.409	1.364	-.157	
	x3	5.623	-.294	-.067	2.270	-.055	
	x4	4.753	-.335	.004	2.862	-.052	
	x5	2.304	-.372	-.020	3.628	.738	
	x6	-.281	-.254	-.183	.038	3.480	
	x7	1.990	-.596	1.050	.500	.611	
Hidden Unit Width		.596	.596	.834	1.114	1.039	
Hidden Layer	H(1)						5.492
	H(2)						-.238
	H(3)						.018
	H(4)						-.483
	H(5)						.297

a. Displays the center vector for each hidden unit.

The RBF network structure has five units of hidden layers as displayed in Fig. 2 and Table 4 gives RBF parameter estimates. Furthermore, Table 5 displays RBF model summary. It seems there were fewer errors in training than that in testing and holding samples. This must be due to the smaller sizes of testing and holdout samples. However, relative errors in testing and holdout samples are quite consistent indicating the RBF model can be used in future with high consistency.

Table 5. RBF model summary

Training	Sum of Squares Error	8.434
	Relative Error	.344
	Training Time	00:00:00.078
Testing	Sum of Squares Error	5.824[a]
	Relative Error	.906
Holdout	Relative Error	.883

Dependent Variable: trip

a. The number of hidden units is determined by the testing data criterion: The "best" number of hidden units is the one that yields the smallest error in the testing data.

Since dependent variable was rescaled by standardization, it has zero mean and unit variance, and, hence, sum of squares total is just equal to $n-1$, where n is the sample size. Corresponding coefficient of determination R^2 can be easily computed as follows. For testing, we have

$$R^2 = 1 - \frac{8.434}{49} = 0.828 \quad \text{and for training} \quad R^2 = 1 - \frac{5.824}{23} = 0.747$$

This shows that RBF performs better than ordinary regression in terms of the amount of variation in dependent variable explained by the model. This is due to flexibility of RBF model.

Finally, from analysis of independent variable importance, see Fig. 3, it is clear that number of students (x_3), number of teachers (x_4), total areas of school and university buildings (x_6) andnumber of offices (x_5) are the most important predictors. This agrees with output of stepwise procedure in regression analysis.

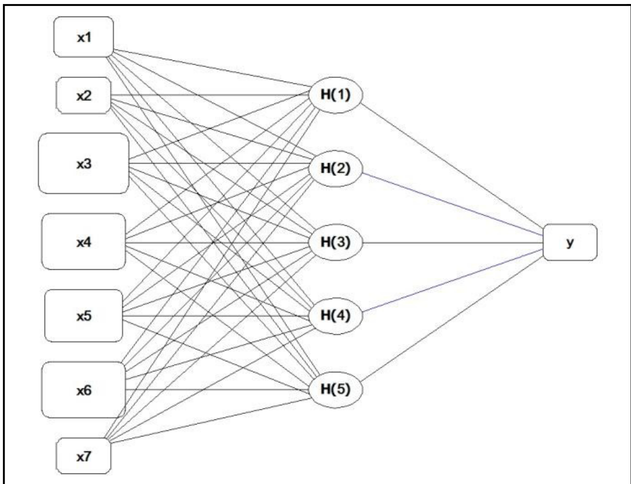

Fig 2. RBF Network Structure

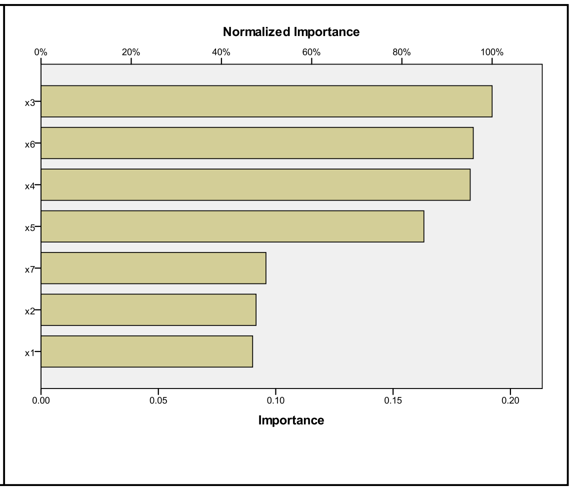

Fig. 3. Importance analysis of predictors

4. Conclusions

The radial basis function neural network model trained to predict trip attraction using seven predictor performs better than ordinary regression model using least square approach. Violation of assumptions for regression model, such as normality of error items and linearity, must be one of the reasons for worse performance of regression model. However, the results from both models show that number of students, number of teachers, total areas of school buildings and number of offices are the most significant predictors for trip attraction.

Appendix A. The Data Used in Analysis

Y : number of vehicles (cars and motorcycles) entering the region during morning rush hours

XI : number of residents

X2 : number of schools/universities

X3 : number of students

X4 : number of teachers

X5 : total areas of school/university buildings

X6 : number of offices

X7 : number of houses

No.	XI	X2	X3	X4	X5	X6	X7	Y
1	9544	6	2919	199	8713.00	3	906	2662
2	3979	2	1326	60	1640.00	1	271	812
3	16498	5	1288	51	4474.00	2	1630	2317
4	19939	12	4720	228	25070.00	9	3717	2971
5	11165	7	2140	128	6700.00	1	3405	121
6	7747	11	3617	267	17200.00	3	1754	1214
7	10474	5	2271	169	10500.00	1	1256	156
S	12175	2	470	28	2200.00	2	2837	572
9	11601	7	1665	133	7000,00	1	2637	552
10	46031	19	28890	1709	45972.81	2	5878	9400
11	5528	1	428	23	1245.64	1	889	2160

No.	XI	X2	X3	X4	X5	X6	X7	Y
44	11453	9	7454	581	10960.12	1	2837	4646
45	14915	5	3261	216	7676,76	1	2751	1186
46	15348	3	1521	43	1678.69	1	2804	657
47	15847	7	4035	245	6429,88		2124	1253
48	10273	7	3527	226	5398.31	1	2026	3574
49	10149	4	2172	90	440.00	1	3995	588
50	10397	8	2707	172	4931.00	I	2146	776
51	6498	5	1692	107	1185.00		1339	1678
52	13791	7	2368	150	3377.00	I	2994	1271
53	7840	3	1015	65	2770.00	1	1786	433
54	20271	11	3721	235	17541.00	1	4147	399

No.	XI	X2	X3	X4	X5	X6	X7	Y
12	32290	6	2604	192	7151.77	3	5625	1997
13	18042	12	4498	331	10339.71	2	3853	2605
14	8235	6	1980	133	8301.51	1	2745	1401
15	23045	13	6129	463	28925.11	2	3270	2539
16	11550	4	1703	77	680.48	1	1633	312
17	13610	4	4038	189	658.68	2	2787	538
18	25958	14	2465	131	2742.38	1	2144	555
19	6289	1	471	21	70.09	1	890	277
20	8798	6	2755	158	781.02	1	1596	277
21	3778	2	984	56	276.00	1	879	789
22	5237	1	360	14	257.00	6	403	527
23	4737	1	360	12	2061.00	1	1031	155
24	5592	5	3438	323	6734.00	2	1401	1776
25	2884	3	1697	221	4518.00	2	689	2906
26	17386	3	1345	64	2103,00	2	4028	1109
27	15077	3	1644	134	2580.00	11	3327	4383
28	15320	6	5688	354	7311.00	8	2072	1731
29	23778	4	3411	455	10676.00	4	4816	1063
30	5497	2	780	49	724.00	1	127	899
31	4050	1	390	24	481.87	1	110	399
32	16126	4	1560	97	1904.00	1	12	571
33	12971	6	2339	147	3784.00	3	233	486
34	5818	6	2339	147	9594.00	8	165	1822
35	23341	19	7408	464	14938.76	1	30	1790
36	11892	2	780	49	1783.00	2	43	1282
37	18316	9	3509	220	3385.92	1	322	2408
38	13290	5	3136	218	4391.42	4	2214	640
39	17187	10	10861	820	82961.34	2	3020	760
40	15245	4	3439	249	4285.00	5	3911	3493
41	17457	9	5048	372	14058.31	3	3235	884
42	22296	11	4616	357	11293.74	1	3151	2404
43	14423	6	2990	145	6248,00	1	2897	3307

No.	XI	X2	X3	X4	X5	X6	X7	Y
55	10769	9	3045	193	6768.00		2733	972
56	16883	5	2679	201	2522.63	1	3821	1229
57	19193	6	2743	182	4218.03	I	4S88	986
58	27395	18	7833	548	41581.67	1	5068	1385
59	5135	1	932	68	111.13	1	1136	313
60	20622	3	1686	165	13581.91		7391	569
61	11350	3	2424	150	775.11		1769	208
62	11876	1	950	56	100.00	1	2685	122
63	10108	3	2850	168	3390.64	1	1450	70
64	21084	5	1515	105	3992.32		4294	52
65	27102	5	3186	204	5798.83		4893	344
66	18410	2	1068	49	193.08	5	1534	849
67	17681	12	16503	1422	51233.86	5	3908	493
68	20622	3	372	54	2959.87		2452	1654
69	12360	5	1674	117	1703.00	I	1457	433
70	12779	4	2104	72	943.00		1860	708
71	15627	6	1721	105	1004.00	4	3016	227
72	21711	14	5688	470	1447.95		4659	1112
73	16635	6	3383	241	4836.40	16	3968	1771
74	26686	8	5197	391	53826.20	4	5819	984
75	14692	4	3439	249	52018.76		3147	2059
76	24713	5	2584	204	15711.61	13	5564	1840
77	10529	9	4122	311	59010.47		2752	499
78	10525	5	3268	236	48417.62	I	3230	1418
79	14603	4	1764	134	27377.34	1	4116	1631
80	23131	3	1847	142	7336.00		3891	778
81	6499	2	1070	67	3000.00		818	190
82	2228	1	300	15	7500.00	1	532	35
83	19566	6	5508	246	11828.78	5	1135	1639
84	18237	5	2589	155	6070.63	17	3816	777
85	26769	2	1172	90	18260.63	2	5669	1001

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