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Estimation of the Percentage of Mainline Traffic Entering Rest Area Based on Bp Neural Network

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Abstract: The percentage of mainline traffic entering is a critical factor for the estimation of the economical benefit and the operation assessment of an existing rest area. This study presents a BP neural network model to predict the percent of mainline traffic entering the rest area for solving the limitations existing in other related methods, including the single factor considered and poor precision. First, seven factors that are considered to affect rest area usage are used as input variables of network and the predicted percent of mainline traffic entering is defined as the output variable. Second, we set up different network structures with different number of neurons in the hidden layer and MSE of results as stopping criteria for getting the best fitting model. Then a network with 7 neurons in input layer, 12 neurons in hidden layer and 1 neuron in output layer, is constructed for the prediction of the percentage entering. The testing result show that the average predicted values of the testing samples have only 1.14% error and the case study also indicates that the predicted value of the model has high reliability.

Key words: Rest area, the entering traffic counts, BP neural network, prediction model

INTRODUCTION

Rest areas perform a critical role in the freeway network. They provide the operators of heavy vehicles and the occupants of passenger vehicles an opportunity to use a restroom, walk around, stop for a meal, sleep for a while, or even pause to use a cellular phone (Al-Kaisy *et al*., 2011). Many of these activities aid in reducing driver fatigue, with the potential for reducing fatigue-related crashes. These various activities also have a direct impact on several aspects of rest area design and management, from parking demand to facility sizing and economical benefit of rest area. All these components are directly influenced by one critical factor: the entering traffic volume, or the percentage of mainline traffic entering the rest area. In summary, information on potential and existing entering traffic volume is critical to the estimation of parking needs, the planning of facilities and the management assessment of the rest area.

The existing literatures on rest area cover a wide variety of aspects, ranging from estimates of traffic counts to estimates of amounts of wastewater and user perceptions. This paper focus on estimating percentage of mainline traffic stopping at a rest area, for example, AASHTO (2001) presented 8-13% of vehicles stop at rest areas along recreational routes and 5.5-9% of vehicles stop along routes with broader use. NCHRP (King, 1989) developed several equations for predicting the percent of mainline traffic that would use a rest area based on the distance between rest areas. Moreover, the elastic coefficient method proposed in the Japanese Expressway Design Standard (JHPC, 1991) is usually employed in China which was to acquire the linear relation between the percentage of different vehicles entering and the growth rate of GDP and the growth rate of freeway mileage. Wang and Tang (2008) proposed a prediction model for the percentage of rest area usage based on the transportation potential theory. Cui and Liu (2008) presented an estimation model based on the vehicle continuous travel time which only considered the spacing interval of rest areas and relied on a large quantity of data about vehicle traveling time.

In fact, if the traffic volume estimates for the rest area is inaccurate, then the prediction of sizing, usage frequency and the operation assessment related to expected life of facilities and economic benefit of rest area based on these figures may be inadequate as well. Moreover, several surveys indicates that the entering traffic volume is affected by multiple factors, including the mainline traffic counts, the spacing intervals of rest areas, trip length, trip purpose and so on. However, it is clear that the foresaid methods mainly considered the single

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factor, for example, the distance between rest areas or the growth rate of freeway mileage, meanwhile, the prediction accuracy is relatively low. In addition, the foresaid methods mainly are used to the planning of the proposed rest area and are scarcely used for the prediction of an existing rest area. For predicting the percentage of mainline traffic entering an existing rest area and giving further data support for the estimation of economic benefit and the assessment related to expected life of facilities to decide the renovation schedule, this paper presents a BP neural network modeling for predicting the percentages of mainline traffic entering the rest area. The paper is organized as follows; Section 1 presents an introduction to the study including the objectives and previous relevant researches. Section 2 contains methodologies used in the paper, including the basic theory of BP network and the details of the input variables and output variable of network. Section 3 trains and test the neural network for getting a best fitting network. Section 4 draws some conclusions about the model and the results of data analysis.

METHODOLOGY

The researches Al-Kaisy *et al.* (2011), Tang (2008), Yin (2009), Rick *et al.* (2011) and Garder and Nicholas (2002) indicated that the entering traffic volume is mainly related to the mainline traffic counts, the distance to upstream or downstream rest area, the development level of local economy, the size of rest area and so on. Obviously, many of these factors have high complexity and nonlinearity and it is hard to show the relationship between them and the percent entering by a simple mathematic formula. However, Artificial Neural Network (ANN) can be an option for solving this type of complex problem, since they are found to be an excellent option for solving many complex issues. Several ANN topologies have been developed for different applications, the most popular is the feed-forward Back-propagation Network (BPNN) which has many advantages, for example, it has simple network structure, is easy to operation and can simulate all kinds of non-linear output/input relations, thus has been widely used to different domains, including intelligent prediction (Valipour *et al.*, 2012), intelligent recognition (James, *et al.*, 2013).

Basic theory of BPNN: The basic BP algorithm includes two aspects: signal forward transmission and error reversed transmission, that is to say, the BPNN computes the actual output values according to the direction from input to output, but the connection weights and threshold values are adjusted according to the direction from output to input. As per the theory that BPNN with three layers (an input layer, an output layer and a hidden layer) can approximate any function very well for the given inputs and the convergence velocity and actual application are considered, a BP neural network with tree layers is constructed in this study, with the factors that are considered to affect rest area usage as the input layer and the predicted value for the percentage mainline traffic stopping as the output layer.

The detailed network structure is given in Fig. 1. P_1 is the input vector to the hidden layer; W_1 and b_1 represent the weight and bias of the hidden layer. The information from the hidden layer is transferred to the output layer, as shown in Fig. 1. The term P_2 represents the output vector and can be determined from the weight, W_2 and bias b_2 of the output layer. The training strategy of the network is shown in Fig. 1, where the input vectors and the corresponding output vectors are used to train the network until it approximates the propagation function.

Selection of input variables: Selection of input variables is a critical part of neural network design. It is possible to use own knowledge of the problem domain to make some selection of variables before starting to use neural networks. In this study, the main objective is to make a correlation of the influencing factors of rest area usage and the percent mainline traffic entering and to provide a model for predicting entering traffic counts using BP neural network. With refer to the related researches Garder and Nicholas (2002) and Rick *et al.* (2011), there are many factors can affect the entering traffic counts and further influence the operation and economical benefit of rest area, but for facilitating data collection, the following factors are assumed to be the input vector of network:

- **Mainline traffic counts:** Owing to the closure of the freeway, the demands of patrons on their way only can be achieved in the rest area, including resting, carting and filling fuel. Generally, the larger of the mainline traffic counts are, the higher demands on the rest area the vehicles need and the more mainline vehicles enter. This is confirmed by Al-Kaisy *et al.* (2011) which presented the average percent mainline traffic entering for the low-volume highways was lower than the average for the high-volume category
- **GDP of city:** On the one hand, the more developed of local economy, the higher transport demands of various social industries; on the other hand, the local economy is closely related to the travel habit of inhabitant and traffic density. This factor is considered in the elastic coefficient method that proposed by the Japanese Expressway Design Standard (JHPC, 1991)

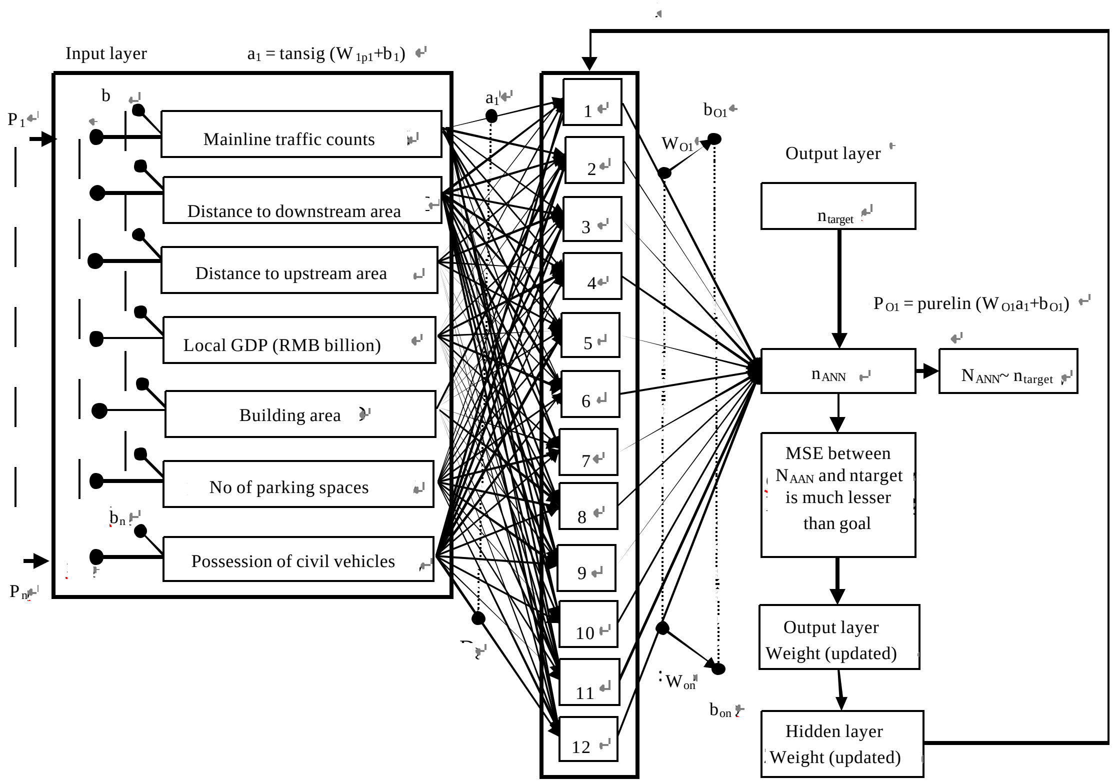

Fig. 1: Structure and training strategy of BP neural network

- **Parking capacity:** The surveys revealed that more parking area there are, the more vehicles they can accommodate. Besides, seeing from the consumer psychology, spacious parking area especially can attract large trucks which take a large proportion in the freeway traffic volumes
- **Building's size:** Generally, the building area is a direct presentation of service ability of rest area, including restroom, gas station, water and sewer system, etc
- **Spacing interval to the upstream and downstream rest area:** Two distance variables are considered for analysis: distance to the nearest upstream rest area and distance to the nearest downstream rest area. It is expected that as each of these distances for a specific rest area increases, the usage of that specific rest area and the percent of mainline traffic entering will increase accordingly. These factors are considered in the work of CDOT (Rick *et al*., 2011), Garder and Nicholas (2002) and Fu *et al*. (2001)
- **Possession of civil vehicles:** The possession of civil vehicles is associated with the travel demand. The increasing travel demand will lead to more trips and more opportunities to use the rest area for having a rest and filling fuel along the trips which can directly affect the usage frequency of rest area

TRAINING AND APPLICATION OF MODEL

Basic information: Xinzheng rest area locates at Zhengzhou-Luohe section of G4 Beijing-Hongkong-Macau Freeway. Due to the viaduct of "Shijiazhuang-Wuhan Passenger Railway" crossed at the entrance ramp and green square of the west of Xinzheng rest area (Fig. 2), the economic benefit coming from the restrooms, fuel stations and restaurants can be affected by disadvantages such as narrowing the entrance width and obstructing the view of the drivers from the freeway, resulting in the decrease of the percentage entering. Obviously, the difference in the entering traffic counts after and before the span of viaduct is a key parameter to decide the impact degree of the viaduct on operations of Xinzheng rest area. For determining the impact degree, the following procedures are assumed to be employed. First, the percent of mainline traffic entering Xinzheng rest area before the span of passenger railway can be predicted based on the proposed model and then the actual percentage of entering after the span of passenger railway can be investigated on the spot. Finally, the difference between the percentage entering before and after the span of viaduct can be utilized to decide the impact degree of Shijiazhuang-Wuhan Passenger Railway on the operation of Xinzheng rest area.

Data collection and analysis: Following the aforesaid procedure, this paper investigated the data of seven input variables at Xinzheng rest area and other nine rest areas that were not influenced by Shijiazhuang-Wuhan Passenger Railway, including the mainline traffic counts (P_1), the distance to upstream rest area (P_2), the distance to the downstream rest area (P_3), the GDP of city the rest area located in (P_4), building's size (P_5) and the parking capacity (P_6), possession of civil vehicles (P_7) and the actual percent of entering, the details can be seen in Table 1. The investigated rest areas are dual ones where facilities are provided in the two directions of travel (i.e., west and east).

Fig. 2: Viaduct of passenger railway crossed the west of Xinzheng rest area at the entrance ramp

Table 2-3 summarize the traffic count data collected in Xinzheng and Yuanyang rest area respectively which are provided using one hour intervals and includes the total number of vehicles, total number of Passenger Vehicles (PVs) and total number of truck along with their percentages. It can be seen that there is a higher percent of passenger vehicles in the daily traffic counts for Xinzheng rest area, excluding two time periods: 7:00-8:00 and 21:00-22:00 while the proportion of passenger vehicles is relatively equal to the percentage of trucks in the traffic volumes of Yuanyang rest area. As for the specific vehicle type, Class 1 and Class 6 have higher percent in the daily entering traffic volumes of rest areas.

Network training and testing: The neural network toolbox of MATLAB 7.11 is used for simulation. The training set includes data of No.1-20 rest area (Table 1), moreover, because of a relatively small sample size, the testing set also includes the data of No.1-20 rest area.

The number of neurons in hidden layer is critical for the performance of the constructed neural network. Usually, the larger the number of neurons in the hidden layer, the better is the performance of the neural network in fitting the data. However, a larger number of neurons in

Table 1: Data of six variables related to ten rest areas

No.	Name	ADT (pcu/d)	Distance to downstream area (km)	Distance to upstream area (km)	GDP (RMB billion)	Building area (m^2)	No. of parking spaces	Possession of civil vehicles (10^4)	Percent entering (%)
1	Anyang (West)	20233	31.90	27.18	268.90	3500	216	6.53	16.49
2	Anyang (East)	20000	27.18	31.90	268.90	3500	215	6.53	16.12
3	Hebi (West)	20236	27.18	96.82	79.62	7500	100	2.52	18.40
4	Hebi (East)	22105	96.82	27.18	79.62	7500	100	2.52	18.10
5	Yuanyang (West)	32418	96.82	24.64	1056.72	9900	290	35.27	27.41
6	Yuanyang (East)	33520	24.64	96.82	1056.72	9900	290	35.27	29.00
7	Zhengzhou East (West)	47926	24.64	28.75	2686.33	4000	122	124.03	26.35
8	Zhengzhou East (East)	46910	28.75	24.64	2686.33	4000	121	124.03	25.85
9	Xinzheng (East)	23484	27.32	28.75	2686.33	4536	95	124.03	12.57
10	Xuchang (West)	28210	27.32	68.70	440.72	3390	142	6.98	18.58
11	Xuchang (East)	27900	68.70	27.32	440.72	3390	142	6.98	18.45
12	Luohe (West)	24399	68.70	52.55	105.46	5935	123	3.14	22.26
13	Luohe (East)	26001	52.55	68.70	105.46	5935	122	3.14	22.87
14	Zhumadian (West)	20001	52.55	62.41	370.10	6670	90	4.47	22.85
15	Zhumadian (East)	19891	62.41	52.55	370.10	6670	90	4.47	21.99
16	Queshan (West)	18300	62.41	53.21	370.10	2340	92	4.47	20.96
17	Queshan(East)	18102	53.21	62.41	370.10	2340	91	4.47	21.07
18	Xinyang (West)	15169	53.21	40.43	315.59	942	70	3.90	16.20
19	Xinyang (East)	15341	40.43	53.21	315.59	901	50	3.90	15.96
20	Lingshan (West)	18972	40.43	19.70	315.59	2918	90	3.90	20.44
21	Lingshan (East)	19201	19.79	40.43	315.59	2917	90	3.90	20.78
22	Xinzheng (West)	24442	28.75	27.32	2686.33	4536	95	124.03	11.77

Table 2: Traffic count data in Xinzheng rest area by vehicle types

Time	Total	#Pv	#Truck	Pv (%)	Truck (%)	Vehicle Classification* 1	2	3	4	5	6
7:00-8:00	35	9	26	25.71	74.29	8	1	2	0	6	18
8:00-9:00	67	42	25	62.69	37.31	39	3	2	2	5	16
9:00-10:00	113	91	22	80.53	19.47	85	6	0	1	3	18
10:00-11:00	131	97	34	74.05	25.95	94	3	5	3	3	23
11:00-12:00	106	71	35	66.98	33.02	66	5	1	4	11	19
12:00-13:00	81	53	28	65.43	34.57	45	8	4	5	2	17
13:00-14:00	105	79	26	75.24	24.76	71	8	2	6	5	13
14:00-15:00	103	73	30	70.87	29.13	63	10	2	4	4	20
15:00-16:00	135	111	24	82.22	17.78	103	8	0	4	6	14
16:00-17:00	117	86	31	73.50	26.50	83	3	4	3	5	19
17:00-18:00	89	59	30	66.29	33.71	54	5	4	1	7	18
18:00-19:00	88	49	39	55.68	44.32	42	7	1	1	6	31
19:00-20:00	64	35	29	54.69	45.31	26	9	1	0	5	23
21:00-22:00	60	24	36	40.00	60.00	23	1	1	2	5	28

*Class 1: passenger car with the recommended seat less than 19, Class 2: passenger car with the recommended seat more than 19, Class 3: trucks with payload capacity less than 2 tons, Class 4: trucks with payload capacity between 2 and 7 tons, Class 5:trucks with payload capacity between 7 and 14 tons, Class 6: trucks with payload capacity more than 14 tons

Table 3: Traffic count data in Yuanyang rest area by vehicle types

Time	Total	#Pv	#Truck	Pv (%)	Truck (%)	Vehicle Classification* 1	2	3	4	5	6
7:00-8:00	114	48	66	42.11	57.89	42	6	2	7	8	49
8:00-9:00	105	58	47	55.24	44.76	52	6	1	3	4	39
9:00-10:00	112	66	46	58.93	41.07	65	1	2	1	6	37
10:00-11:00	112	71	41	63.39	36.61	70	1	6	4	4	27
11:00-12:00	149	67	82	44.97	55.03	59	8	18	2	6	56
12:00-13:00	162	106	56	65.43	34.57	97	9	2	5	4	45
13:00-14:00	153	105	48	68.63	31.37	98	7	3	0	5	40
14:00-15:00	162	89	73	54.94	45.06	81	8	10	2	4	57
15:00-16:00	123	72	51	58.54	41.46	70	2	3	4	4	40
16:00-17:00	183	121	62	66.12	33.88	116	5	4	4	13	41
17:00-18:00	131	80	51	61.07	38.93	75	5	3	1	4	43
18:00-19:00	119	60	59	50.42	49.58	57	3	2	3	4	50
19:00-20:00	107	51	56	47.66	52.34	49	2	2	1	3	50
21:00-22:00	76	37	39	48.68	51.32	32	5	2	3	2	32

the hidden layer will sometimes result in the problems of over-fitting and overtraining that may reduce the performance of neural networks in predicting the targets. For getting a best fitting model, the network structure is varied starting with 5 neurons in the hidden layer and, after several trials, the model with 12 neurons in the hidden layer is found to be successful in predicting the targets both in the training and testing set, where the initial number of neuron in the hidden layer is determined by an empirical formula:

$$l = \sqrt{0.43mn + 0.12n^2 + 2.54m + 0.77n + 0.35} + 0.51$$

(m, n are the number of neuron in the input layer and output layer, respectively). Meanwhile, "tansig" and "purelin" are used as the transfer functions in the hidden layer and in the output layer, respectively. The "traingdx" function is used to train the network, the "learngdm" is used as the adaption learning function and the performance of network is measured by MSE. net.trainParam.epochs = 3000, net.trainParam.lr = 0.01, net.trainParam.goal= 0.0005. Finally, a best fitting network is constructed, composed of an input layer with 7 neurons and a hidden layers with 12 neurons and an output layer with 1 neuron (7×12×1). The detailed structure of the network can be seen in Fig. 1.

If the total number of data in the training set is much larger than the number of parameters in the neural network, then there is little or no chance of over-fitting. However, due to limited resources, it is difficult to increase the size of training data set and fortunately an "Early Stopping" technique can be used to prevent over-fitting automatically. As shown in Fig. 3, with the "Early Stopping" technique, training on the training set continues as long the training reduces the network's validation error. After the network begins to overfit the training set (at epoch 140), the validation error typically begins to rise. Fig. 3 also shows the training, validation and testing result have the small final MSE and without any significant over-fitting occurring. Therefore, the

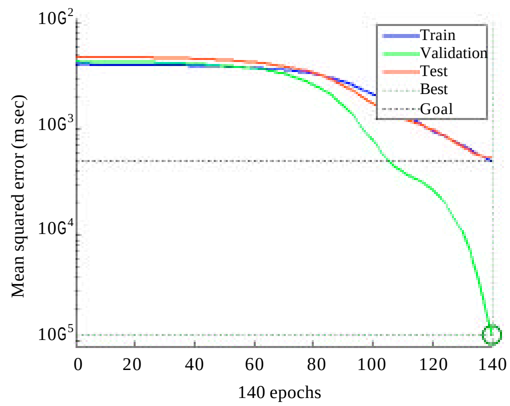

Fig. 3: Performance of the BP neural network

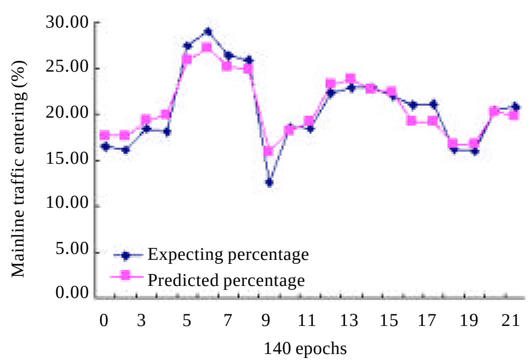

Fig. 4: Predicted and expected value of testing set

training BP neural network at epoch 140 is reasonable and acceptable. The predicted and expected values of the testing set are shown in Fig.4; shows the errors of predicted value are very small.

DISCUSSIONS

The data of the west of Xinzheng rest area is inputted into the model and the predicted percent entering provided by the proposed model is equal to 13.85%. Because it is obtained by BP network based on the data from nine rest areas that were not affected by the viaduct of passenger railway, it can be considered as the theoretical value under the impact of seven variables before railway spanning cross the west of Xinzheng rest area.

Besides, the predicted value is similar to the percent (13%) that presented in the Feasibility Report of Xinzheng Rest Area Planning. It indicates that the predicted value has high reliability and can reflect the expected value before the spanning of railway. Finally, comparing the predicted and the actual percentage of mainline traffic entering at Xinzheng rest area (11.77%, as shown in Table 1) after the spanning of railway, the latter is reduced by 2.08% which can be used to determine the impact degree of the span of Shijiazhuang-Wuhan Passenger Railway on the west of Xinzheng rest area and can be further used for the future estimation of economic loss.

CONCLUSION

- The percent of mainline traffic entering is critical to the estimation of the economic benefit and the operation assessment of an existing rest area. It is mainly affected by the factors including the mainline traffic counts, the GDP of city, the distance to the nearest upstream rest area and distance to the nearest downstream rest area and so on. The analyses show that the factors investigated vary in a broad range and only explain some of the variation in the usage frequency of rest area. Specifically, variables such as trip length and traffic composition (local versus non-local drivers) may also affect the percentage entering, yet are not studied in this paper, primarily for reasons related to data availability and required resources
- The correlation between the entering mainline traffic and seven variables can not be generated using a simple regression analysis and then a BP neural network with tree layers is employed for modeling the correlation. Meanwhile, we set up different network structures with different number of neurons in the hidden layer and MSE of results as stopping criteria for getting the best fitting model. Finally, a model with 7 neurons in the input layer, 12 neurons in the hidden layer and 1 neuron in the output layer is found to be successful in predicting the targets both in the training and testing set. The testing results show that the average predicted values of the testing samples have only 1.14% error. The case study also shows that the predicted value of the proposed model has high reliability

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