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Computational Experiments for Studying Impacts of Land Use on Traffic Systems

Yan Ou, Shuming Tang, *Member, IEEE*, and Fei-Yue Wang, *Fellow, IEEE*

Abstract—**This paper investigates the impacts of land use on traffic systems through computational experiments based on TransWorld, a computational platform for artificial transportation systems. First, we introduce the components of TransWorld and their functions. Second, for given a road network, we employ factorial design and regression to analyze whether and to what extent that the factors of land use have impacts on traffic systems. Three factors, i.e., residential density, distribution type, and attraction ratio, are involved in the related computational experiments during a period from 6:00am to 12:00am. The average speed of vehicles on the road network is used as the performance index to evaluate traffic conditions. Computational experimental results have indicated that all three factors and their interactions have significant effects on traffic systems.**

I. Introduction

At present, China has been in the mid-acceleration phase of urbanization. As it is predicted, there will be 12 million people becoming urban residents annually in China [1]. Meanwhile, coupled with the ever increasing purchasing power of city dwellers, car ownership in the city has been rapidly soaring, whereas growing traffic demands have imposed great pressure on urban transportation. Generally speaking, different traffic demands correspond to different land use distributions, attributes, and densities [2]–[3].

Although scientific and policy debate has been continued for years, there is still no consensus about impacts of land use on traffic systems. Bert van Wee [4] provides a comprehensive review of researches about land use impacts on traffic systems. The review shows that researchers' opinions are different with respect to the possible impacts of land use on transport because they adopted different experiment conditions in their individual research. Some studies conclude that land use may have a significant impact on traffic systems, while others find marginal or little impact. Nevertheless, a relatively strong consensus is achieved about the most important factors that may affect traffic system, such as densities, mixed land use, and neighborhood design.

Lawrence D. Frank and Gary Pivo [5] carried out their research on the impacts of mixed land use, population density, and employment density on the use of the single-occupant vehicle, transit, and walking for both work trips and shopping trips. Findings showed that density and mixed land use are both related to mode choice, and has a positive impact on traffic systems. A research of Badoe and Miller [6] also supports the positive impact of land us on traffic systems.

Kenneth Joh [7] conducted a case study in the south bay area of Los Angeles to investigate relationships between land use and travel behavior. The results indicated that mixed-use neighborhoods promote walking trips rather than reducing automobile trips, and have an effect on traffic systems.

Marlon Boarnet and Randall Crane [8] researched the influence of land use on travel behavior. They adopted the income level of the individual, gender, education level, and urban design characteristics near the residences of the individual as independent variables, and fitted the model on two data sets. The statistical results suggested a tendency that dense street networks were associated with less non-work car trips, and households living further from the central business district tended to make more non-work car trips.

Henk Meurs and Rinus Haaijer [9] studied the extent to which spatial structure and spatial planning of the residential environment have effects on mobility and the choice of mode in traffic systems. They found significant impacts of neighborhood design on travel behavior, and indicated that reduced car mobility could be achieved when facilities for daily and other shopping and schools were located close to the home, or the road network in the neighborhood was laid out for travelling by bike or on foot.

Artificial Transportation Systems (ATS) is a natural extension of computer simulations for analysis and decision supporting of traffic systems. ATS adopts agent-based and bottom-up integrated research methods [10]–[12]. By making use of extraction of basic law from individual or local transport behavior, it helps observing and understanding the complex transportation phenomenon that emerged from interactions among the various components of traffic systems, as well as the development and characteristics of traffic systems as a whole. Based on the ATS ideas, a platform, TransWorld, is developed by the Complex Adaptive Systems for Transportation (CAST) laboratory [13].

Computational experiments, the basic concept of which is

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Yan Ou is with the Key Laboratory of Complex Systems and Intelligence Science (KLCSIS), Institute of Automation, Chinese Academy of Sciences (CASIA), Beijing, 100190, China. (e-mail: ouyan2007 @gmail.com).

Shuming Tang is a Taishan Chair Professor of Shandong University of Science and Technology and is a research professor and director of Lab of Complex Adaptive Systems for Transportation at CASIA, Beijing, China. (e-mail: sharron@ieee.org).

Fei-Yue Wang is the vice president of CASIA and a director and professor at KLCSIS, Chinese Academy of Sciences, Beijing, 100190, China. He is also affiliated with the university of Arizona, Tucson, U.S.A. (e-mail: feiyue.wang@ia.ac.cn).

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not to simply view computer as a tool for simulation, but rather treat it as library to "foster and grow" alternative version of actual system [14]–[15]. Computational experiments employ the ideas and methods of artificial system to generate and analyze complex behaviors by means of computational simulation and observation based on emergence. Further, numerical methods can be used for effective assessment of decision-making.

The purpose of this paper is to study impacts of land use on traffic systems based on the TransWorld platform. Given a road network, we employ factorial design and regression to analyze whether and the extent to which that the factors of land use have impacts on traffic systems. There are three factors, residential density, distribution type, and attraction ratio, are involved in the related computational experiments during 6:00am to12:00am. The average speed of vehicles on the road network is used as the performance index to evaluate traffic conditions.

The paper is organized into four sections. First, Section II briefly introduces the TransWorld platform, since data of experiments are obtained on this computational platform. Next, Section III presents the experimental conditions and employs factorial design to explore qualitatively whether the factors of land use have effects on traffic systems. Then, in Section IV, we propose a regression expression to analyze quantitatively those impacts on road network traffic conditions. Finally, Section V concludes this paper and discusses future work to be done.

II. THE TRANSWORLD PLATFORM

The TransWorld platform is a computational platform and emphasizes on the effects of rules and autonomy of individuals [16]. This platform is composed of network construction module, artificial population generation module, microscopic traffic simulation module, two-dimensional (2D) and three-dimensional (3D) animated display modules. It can be used to make simulation, evaluation and optimization to the potential traffic planning, management and control strategies used in real traffic systems.

The network construction module is for the purpose of plotting fundamental topology structure and configuring basic information of road network. This module is able to manifest land use conditions by setting attributes of activity places, which include the location, types, and capacity.

Artificial population generation module is used to generate dynamic population and individual's daily activity plan. By integrating total number of population, percentage of persons at different age group and gender, and other parameters, we can generate artificial population as one of inputs to a computational experiment. In addition, population is renewed by birth rate and death rate [17].

Microscopic traffic simulation module is applied to simulate the movement of vehicles and travelers on a network [18]. Agents in the TransWorld platform execute their activities based on the plans provided by artificial population generation module. Agents' travel behavior on a network primarily includes route choosing, learning, car following, and lanes changing, etc.

2D and 3D animated display modules aim at demonstrating the evolution process of traffic conditions vividly and intuitively. Both of modules are able to show from the macroscopic view of a whole road network to the microscopic view of vehicle movement corresponding to the zoom ratio, as shown in Fig.1 and Fig.2. In Fig.1, the rectangles with different colors denote different types of activity places, and the road sections in different colors denote different congestion states, specifically, green means traffic runs smoothly, yellow means vehicles on network move slowly, and red means road network is crowded.

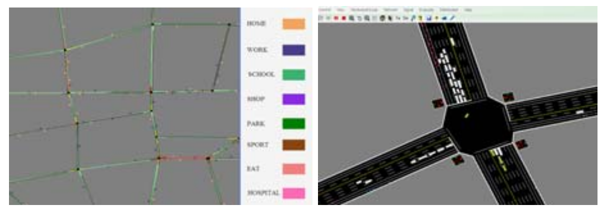


Fig.1 The 2D images in the TransWorld platform


Fig.2 The 3D images in the TransWorld platform

We can get the density, velocity of the road by placing detectors on network, thus plot the density-velocity curve shown in Fig.3. The curve basically conforms to the empirical one obtained from the real traffic system. It indicates that the traffic flow originated from the TransWorld platform can comply with the inherent laws of traffic systems in real world. Therefore, the analysis results of computational experiments based on the TransWorld platform help to the control and management of real traffic systems.

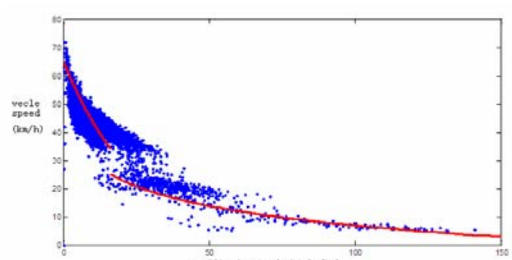


Fig.3 The density-velocity curve obtained from the TransWorld platform

III. FACTORIAL DESIGN

Computational experiments embrace experimental design and data analysis. Their design should follow three basic principles: replication, randomization, and blocking [19].

The scope of the road network studied in this paper covers 255 km^2, within the Second Ring of Jinan, in Shandong

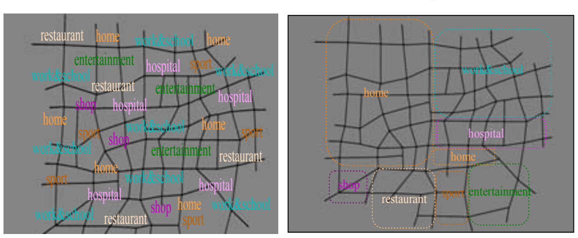
Province of China. This area is north to Beiyuan Avenue, south to Jing 10 Road, west to Wei 12 Road, east to Lishan Road, almost covering the central urban area of Jinan city. There are eight types of activity places, that is, residential communities, office buildings, schools, shopping malls, hospitals, restaurants, sports sites and recreational facilities.

As to factors, obviously, there is not only one factor of land use affects traffic systems. Factorial design can simultaneously estimate the effects on the response, which are caused by all possible combinations of the levels of factors. In this paper, we adopt factorial design because it is an efficient method to study the effects of more than one factor on the response to an experiment.

Generally, densities, mixed land use, and neighborhood design are treated as the most important factors that may affect traffic system in the studies on the impacts of land use on traffic systems. Therefore, those three factors are adopted in this paper. The meanings and levels of three factors are explained specifically as follows.

As we know, one can choose residential density, household density, or job density as a substitute index of "density". In this paper, the residential density is used, which is defined as how many persons live in each square kilometer of the network. Supposing the total number of residents in the researched network is 50000, 100000, and 150000, three levels of residential density are available: 196 persons/ km^2, 392 persons/ km^2, and 588 persons/ km^2.

As to mixed land use, we adopt distribution type as a detailed index, the meaning of which is the distribution of different kinds of activity places. We define two types of land use in our experiment. The first one is dispersed distribution, in which various places scatter in the network, as shown in Fig.4 (a). The second one is clustered distribution, as shown in Fig.4 (b). In this second type, places of the same type concentrate on a certain region. For both of two distribution types, different colors denote different kinds of places. Each of these two distribution types includes 163 residential communities, 88 office buildings, 59 schools, 19 shopping malls, 21 hospitals, 37 restaurants, 10 sports sites and 13 recreational facilities. In total, there are 410 places.



(a) Dispersed distribution (b) Clustered distribution

Fig.4 Two types of distribution

As to neighborhood design, we take attraction ratio as an index, which represents to what extent does the neighborhood circumstances attract people to travel by car. In our experiment, this factor has two values: 0.1 and 0.9, which relatively indicate that it is expected to be 10% and 90% of travelers taking their trips by car.

As a conclusion, in our factorial design experiment, we take residential density, distribution type, and attraction ratio as variables and the response is the average speed of vehicles on the road network. Our computational experiments on factorial design on each factor are done in one block and conducted repeatedly twice during 6:00am to12:00am. Besides, all the 24 tests are arranged in random order.

By running the TransWorld platform, the response can be obtained as shown in Table 1. The numbers in brackets mean the order of trials in this experiment.

TABLE 1

AVERAGE SPEED OF VEHICLES DURING 6:00AM-12:00AM(KM/H)

Residential Density (A)	Distribution Type (B)			
	Dispersed		Clustered	
	Attraction Ration(C)		Attraction Ration(C)	
	0.1	0.9	0.1	0.9
196	41.711(10) 41.397(20)	37.964(17) 38.001(22)	39.253(2) 39.539(4)	26.923(9) 25.561(12)
392	39.948(1) 40.246(19)	29.248(15) 28.532(21)	33.483(6) 33.484(16)	16.217(3) 16.497(24)
588	38.403(7) 38.269(11)	17.396(8) 17.328(18)	27.721(5) 27.490(13)	13.013(14) 12.515(23)

Grouped histograms are drawn by MINITAB to compare the effect of each factor at all levels on average speed, as shown in Fig.5. Take residential density for example, the average speed under 588 persons/ km^2 is about 24 km/h, which is the lowest among three levels of residential density(30 km/h for 392 persons/ km^2; 36 km/h for 196 persons/ km^2). In contrast, average speed under 196 persons/ km^2 has higher mean value and shorter deviation.

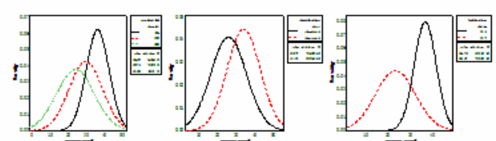


Fig.5 Grouped histogram for residential density, distribution type, and attraction ratio

Such graphs are commonly very useful in interpreting significant interactions. However, they can't be utilized as the sole method because their interpretation may be inaccurate. Thus statistical method will be employed to explain the relationship among the response and the variables.

Define residential density as Factor *A*, distribution type as Factor *B*, and attraction ratio as Factor *C*. Where Factor *A* has *a* levels, Factor *B* has *b* levels, Factor *C* has *c* levels, and the complete experiment is replicated *n* times. As usual, we use the following effect model to express the model of a factorial experiment in this paper.

$$y_{ijkl} = \mu + \tau_i + \beta_j + \gamma_k + (\tau\beta)_{ij} + (\tau\gamma)_{ik} + (\beta\gamma)_{jk} + (\tau\beta\gamma)_{ijk} + \varepsilon_{ijkl}$$

i=1,2,..,a; j=1,2,…,b; k=1,2,..,c; l=1,2,..n,

where μ is the overall mean effect; τ_i is the effect of the ith level of Factor *A*; β_j is the effect of the jth level of Factor *B*; γ_k is the effect of the kth level of Factor *C*; $(\tau\beta)_{ij}$ is the effect of interaction between τ_i and β_j; $(\tau\gamma)_{ik}$ is the effect of interaction between τ_i and γ_k; $(\beta\gamma)_{jk}$ is the effect of interaction between β_j

and γ_k; $(\tau\beta\gamma)_{ijk}$ is the effect of interaction among τ_i, β_j, γ_k; and ε_{ijkl} is a random error.

The hypotheses tested are the equality of main effects and whether interaction effects exist. Their detailed information is as follows.

H_{01}: $\tau_1=\tau_2=\ldots=\tau_a=0$, H_{11}: at least one $\tau_i\neq 0$
H_{02}: $\beta_1=\beta_2=\ldots=\beta_b=0$, H_{12}: at least one $\beta_j\neq 0$
H_{03}: $\gamma_1=\gamma_2=\ldots=\gamma_c=0$, H_{13}: at least one $\gamma_k\neq 0$
H_{04}: $(\tau\beta)_{ij}=0$, for all i, j, H_{14}: at least one $(\tau\beta)_{ij}\neq 0$
H_{05}: $(\tau\gamma)_{ik}=0$, for all i, k, H_{15}: at least one $(\tau\gamma)_{ik}\neq 0$
H_{06}: $(\beta\gamma)_{jk}=0$, for all j, k, H_{16}: at least one $(\beta\gamma)_{jk}\neq 0$
H_{07}: $(\tau\beta\gamma)_{ijk}=0$, for all i, j, k, H_{17}: at least one $(\tau\beta\gamma)_{ijk}\neq 0$

Now, three-factor analysis of variance is employed to test these hypotheses. Suppose SS_A, SS_B, SS_C are the sums of squares for the main effects of Factors *A*, *B*, and *C*; SS_E is the sum of squares for the error; SS_T is the total corrected sum of squares; SS_{AB}, SS_{AC}, SS_{BC} are the sums of squares for the two-factor interactions; SS_{ABC} is the sum of squares for the three-factor interaction; and $SS_{Subtotals}$ is the sum of squares between the total *abc* cell.

The degree of freedom for any main effect is the number of levels of the factor minus one, and the degree of freedom for an interaction is the product of degrees of freedom of each individual factor. Each sum of squares divided by its degree of freedom is a mean square, individually as MS_A, MS_B, MS_C, MS_{AB}, MS_{AC}, MS_{BC}, MS_{ABC}, and MS_E.

Table 2 shows some data analysis results for the factorial design in this experiment. Here, y_{ijkl} denotes the observed response when Factor *A* is at the *i*th level, Factor *B* is at the *j*th level, and Factor *C* is at the *k*th level for the *l*th replicate. $y_{i\ldots}$ denotes the total of all observations under the *i*th level of Factor *A*. $y_{.j..}$ denotes the total of all observations under the *j*th level of Factor *B*. $y_{..k.}$ denotes the total of all observations under the *k*th level of Factor *C*. $y_{ij..}$ denotes the effect of the interaction between Factors *A* and *B*. $y_{.jk.}$ denotes the effect of the interaction between Factors *B* and *C*. $y_{i.k.}$ denotes the effect of the interaction between Factors *A* and *C*. $y_{\ldots.}$ denotes the grand total of all the observations.

Therefore, we can calculate the sums of square in Table 3 according to Eq. (1)-(6).

$$SS_T=\sum_{i=1}^{3}\sum_{j=1}^{2}\sum_{k=1}^{2}\sum_{l=1}^{2}y_{ijkl}^2-\frac{y_{\ldots.}^2}{abcn}, \quad (1)$$

$$SS_A=\sum_{i=1}^{3}\frac{y_{i\ldots}^2}{bcn}-\frac{y_{\ldots.}^2}{abcn},\ SS_B=\sum_{j=1}^{2}\frac{y_{.j..}^2}{acn}-\frac{y_{\ldots.}^2}{abcn},\ SS_C=\sum_{k=1}^{2}\frac{y_{..k.}^2}{abn}-\frac{y_{\ldots.}^2}{abcn}, \quad (2)$$

$$SS_{AB}=\sum_{i=1}^{3}\sum_{j=1}^{2}\frac{y_{ij..}^2}{cn}-\frac{y_{\ldots.}^2}{abcn}-SS_A-SS_B,$$

$$SS_{AC}=\sum_{i=1}^{3}\sum_{k=1}^{2}\frac{y_{i.k.}^2}{bn}-\frac{y_{\ldots.}^2}{abcn}-SS_A-SS_C,$$

$$SS_{BC}=\sum_{j=1}^{2}\sum_{k=1}^{2}\frac{y_{.jk.}^2}{an}-\frac{y_{\ldots.}^2}{abcn}-SS_B-SS_C, \quad (3)$$

$$SS_{ABC}=\sum_{i=1}^{3}\sum_{j=1}^{2}\sum_{k=1}^{2}\frac{y_{ijk.}^2}{n}-\frac{y_{\ldots.}^2}{abcn}-SS_A-SS_B-SS_C-SS_{AB}-SS_{AC}-SS_{BC}, \quad (4)$$

$$SS_{subtotals(ABC)}=\sum_{i=1}^{3}\sum_{j=1}^{2}\sum_{k=1}^{2}\frac{y_{ijk.}^2}{n}-\frac{y_{\ldots.}^2}{abcn}, \quad (5)$$

$$SS_E=SS_T-SS_{subtotals(ABC)}. \quad (6)$$

Then, the analysis of variance is summarized in Table 3.

TABLE 2
SOME DATA ANALYSIS RESULTS FOR THE FACTORIAL DESIGN

Residential Density (A)	Distribution Type(B): Dispersed, Attraction Ration(C) 0.1	Dispersed, 0.9	Clustered, Attraction Ration(C) 0.1	Clustered, 0.9	yi…
196	41.711 41.397	37.964 38.001	39.253 39.539	26.923 25.561	290.349
392	39.948 40.246	29.248 28.532	33.483 33.484	16.217 16.497	237.655
588	38.403 38.269	17.396 17.328	27.721 27.490	13.013 12.515	192.135
$y_{.jk.}$	239.974	168.469	200.970	110.726	$y_{\ldots.}$=720.139
$y_{.j..}$	408.443		311.696		

A	A*B Totals y_{ij} B: Dispersed	Clustered	A*C Totals $y_{i.k.}$ C: 0.1	0.9
196	159.073	131.276	161.900	128.449
392	137.974	99.681	147.161	90.494
588	111.396	80.739	131.883	60.252

TABLE 3
ANALYSIS OF VARIANCE

Source of Variation	Sum of Squares	Degree of Freedom	Mean Square	F_0
A	603.947	2	301.974	2415.792
B	389.999	1	389.999	3119.992
C	1090.1	1	1090.1	8720.8
AB	7.361	2	3.681	29.448
AC	92.526	2	46.263	370.104
BC	14.631	1	14.631	117.048
ABC	67.582	2	33.791	270.328
Error	1.5	12	0.125	
Total	2267.7	23		

The model contains three main effects, three two-factor interaction effects, and one three-factor interaction effect. As the F_{0A} value (2415.792) for the effect of residential density on average speed is more than 6.93 ($F_{0.01,\ 2,\ 12}$), there is evidence of a significant effect. Similarly, the main effects of distribution type and attraction ratio are also significant. Hence, all three main effects are significant at the 0.01-level.

In the same way, the F_{0AB} value is more than 6.93($F_{0.01, 2, 12}$), so there is evidence that effect of residential density on average speed depends on distribution type. Similarly, it can be concluded that there is a significant interaction between residential density and attraction ratio, also between distribution type and attraction ratio, as well as among these three factors. Hence, all four-group interaction effects are significant at the 0.01-level. Consequently, it doesn't need to refit the model to exclude non-significant interactions.

Furthermore, factorial plots are exploited to visualize how the three factors affect the response, as shown in Fig.6. Factorial plots make up of main effect plots and interactions plots. Main effect plots display the mean response at each level of each factor, while interactions plots display the mean response at each combination of levels of any two factors.

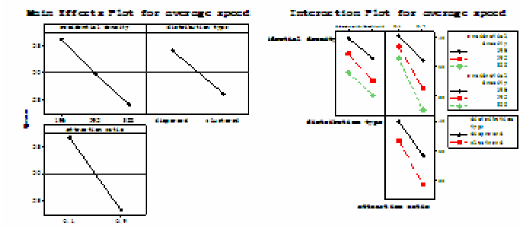


Fig.6 Factorial plots for response

From Fig.6, the lines in main effect plots are not horizontal, indicating that the response does change depending on the levels of factors. Moreover, main effect plots show that higher residential density or attraction ratio, or clustered distribution type results in lower average speed. In addition, the slope of the line for attraction ratio is greater, thus the effect of attraction ratio is the strongest among the main factors. Similarly, the lines in interactions plots are either not horizontal, indicating that the response does change depending on each combination of levels of any two factors. Besides, the interaction effect of residential density and attraction ratio is the strongest among the interaction effects. Concerning the three-factor interaction effect, Table 2 shows that average speed is the lowest (12.515 km/h) when residential density is 588 persons/ km^2, distribution type is clustered distribution, and attraction ratio is 0.9, while residential density at 196 persons/ km^2, dispersed distribution, and attraction ratio at 0.1 make the highest average speed (41.711 km/h). These conclusions conform to the results of earlier analysis in our factorial design experiments.

Since analysis of variance in factorial design has to meet such three assumptions: 1) the errors are normally distributed with mean zero, 2) constant variance for different levels of a factor or according to the values of the predicted response, and 3) each error is independent of all other errors. If these assumptions are violated, the results of the analysis may be misleading. Therefore, we have to check the validity of these assumptions through residuals plots shown in Fig.7.

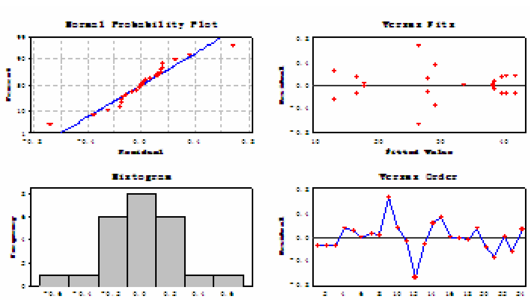


Fig.7 Residual plots for average speed of vehicle

In Fig.7, the normal probability plot roughly follows a straight line, which indicates that the response data are normally distributed. In the residuals versus fits plot, the residuals are scattered randomly about zero, and it indicates that the variance is basically constant. The histogram shows there are basically no outliers. In the residuals versus order plot, the residuals fluctuate in a random pattern around a center line, which indicates the response data have nothing to do with time or order of our experiments. As a conclusion, the residuals don't indicate any major concerns, and analysis of variance in factorial design meets the assumptions.

IV. Regression Analysis

Regression models are very useful when one or more of the factors in an experiment are quantitative. In this paper, we make linear regression experiments to investigate the relationship between average speed and those three factors. In this part of experiments, two quantitative variables (residential density and attraction ratio) and one qualitative variable (distribution type) are treated as independent variables. Hereinto, the distribution type can be treated as a dummy variable, that is, 0 denotes dispersed and 1 denotes clustered.

From above factorial design, we find the main effects of three factors are more significant than the interaction effects, so firstly, we construct a linear regression model. Thus, a regression equation of a three-factor experiment can be written as

$$Y = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \alpha_3 D,$$
$$D = 0, \text{ dispersed distribution;}$$
$$D = 1, \text{ clustered distribution,} \tag{7}$$

where Y is the response; $\alpha_0, \alpha_1, \alpha_2, \alpha_3$ are parameters whose values are needed to be determined; X1 is a variable that represents residential density; X2 is a variable that represents attraction ratio; and D is a variable that represents distribution type.

By running the TransWorld platform, data can be obtained shown in Table 4. The statistical software SPSS (Statistical Program for Social Sciences) is used for regression analysis, as shown in Table 5.

From Table 5, we could get the regression equation is estimated as Eq. (8).

$$Y = 52.05 - 0.026X_1 - 17.014X_2 - 8.974D. \tag{8}$$

TABLE 4
Data for Average Speed of Vehicles on Network

Y	X_1	X_2	D	Y	X_1	X_2	D
42.264	78	0.2	0	39.396	196	0.1	1
41.004	156	0.3	0	26.242	196	0.9	1
39.641	196	0.5	0	33.484	392	0.1	1
41.554	196	0.1	0	16.357	392	0.9	1
37.983	196	0.9	0	27.606	588	0.1	1
36.798	275	0.6	0	12.764	588	0.9	1
40.097	392	0.1	0	43.014	39	0.1	1
28.89	392	0.9	0	28.733	235	0.6	1
27.141	431	0.8	0	20.815	314	0.7	1
38.336	588	0.1	0	14.601	471	0.8	1
17.362	588	0.9	0	21.187	196	0.5	1

TABLE 5
REGRESSION ANALYSIS IN THE EXPERIMENT

(a)MODEL SUMMARY

Model	R	R^2	Adjusted R^2	Std. Error of the Estimate	Durbin-Watson
1	0.942	0.887	0.869	3.635034	1.567

(b)ANOVA

	Sum of Squares	df	Mean Square	F	Sig.
Regression	1873.622	3	624.541	47.265	.000
Residual	237.842	18	13.213		
Total	2111.464	21			

(c)COEFFICIENTS

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std.Error	Beta		
Constant	52.050	2.016		25.822	.00
X_1	-.026	.005	-.436	-5.365	.00
X_2	-17.014	2.388	-.580	-7.124	.00
D	-8.974	1.552	-.458	-5.783	.00

Table 5 indicates that those three predictors (attraction ratio, residential density, and distribution type) have significant effect on the response (average speed). Furthermore, the predictors can explain 88.7% of variation in the observed response values (as we know that the higher of the R^2 in Table 5, the better of the fitting results. Generally, value larger than 0.8 indicates the model is satisfactory). Eq. (8) suggests that higher attraction ratio or higher residential density leads to lower average speed. As to distribution type, by transforming into dummy variable, we could conclude from the regression expression that the average speed under clustered distribution is lower (8.974 km/h lower than dispersed distribution). Besides, attraction ratio has the greatest effect on average speed. When the attraction ratio increases by one unit, the average speed decreases more (17.014 km/h). Finally, plots of residuals shown in Fig.8 indicate that the regression model meets the assumptions of normality and constant variance.

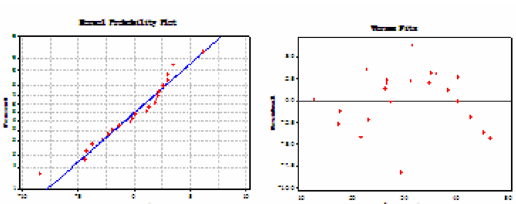


Fig.8 Plots of the residuals for regression

V. CONCLUSIONS

This paper uses the TransWorld platform to study impacts of land use on traffic conditions under given road network. Set residential density, distribution type, and attraction ratio as factors related to land use, and take average speed of vehicle on the road network during 6:00am to 12:00am as response, we employ factorial design and regression to analyze the impacts of land use on traffic systems. The results indicate that all of three factors have significant main effects, and the interaction effects are all significant but less than main effects. Moreover, as to quantitative variables, higher value of each factor results in lower response, while as to qualitative variable, dispersed type is associated with higher response. The next work to be done includes using more indicators to comprehensively evaluate traffic conditions on the road network. In addition, we will enlarge the sample size to find a model that can be applied in a larger scale. Some improvements of the functions of the TransWorld platform are also very meaningful.

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