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Impact of Evacuee Behavior on Evacuation Clearance Time*

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***Abstract* - Evacuation is an effective strategy to mitigate damage of man-made or natural disasters. Evacuation clearance time is one of the key indicators in evacuation planning and management. Evacuees' destination choice and route choice behavior are two crucial factors used to estimate evacuation clearance time. However, these two factors are viewed as constants in previous research, and the quantification of the impact of these two factors is lacking. In this paper, the authors report impact of variation of evacuees' destination choice and route choice behavior on evacuation clearance time. The impact analysis is done based on a case study by using an artificial transportation system platform called TransWorld. And the best values of evacuees' destination choice and route choice behavior are given, respectively. The computational experimental results illustrate that if evacuation managers adopt reasonable strategies to guide evacuees' destination choice and route choice, it can significantly reduce evacuation clearance time. The simulation methodology, computational results and discussion can be used for future emergency evacuation planning. This study also provides potentials of new emergency evacuation management and control strategies from the perspective of evacuee behavior.**

Index Terms - Emergency Evacuation, Evacuee Behavior, Computational Experiments, Evacuation Clearance Time.

I. INTRODUCTION

Natural or man-made disasters such as hurricanes and terrorist attacks can cause huge loss of life and property. Evacuation is an effective response to mitigate damage of various disasters. It is necessary to consider evacuee behavior under emergency conditions in emergency planning because evacuee behavior has a significant impact on emergency evacuation planning, management and control.

Stern and Sinuany-Stern developed a simulation model incorporating behavioral factors including the diffusion time of the evacuation instructions and individual's evacuation decision time in emergency planning [1]. Dow and Cutter analyzed the impact of household decisions on evacuation in Hurricane Floyd, in which they considered the timing of departure and the role of information in the selection of specific evacuation routes [2]. Murray-Tuite developed two linear integer programming models to describe a family's meeting location selection process and trip chains for drivers to pick up family members who may not have access to vehicles [3]. Stopher et al. and Alsnih et al. developed multinomial and mixed logit models to determine when a household would evacuate due to bush fires [4]-[5]. Lazo et al. used the stated-choice valuation method to study households' evacuation decision [6]. Chiu et al. developed a real-time traffic management system for evacuation. They considered evacuee responses to management strategies [7]. Further, Chiu et al. proposed a behavior-robust feedback information routing strategy to improve system performance [8]. Li et al. simulated pedestrian evacuation using Vissim, in which they considered the spatial distribution of pedestrians [9]. Hu et al. proposed a minimum-safety-distance-based evacuation car-following model by improving the Gipps car-following model, in which they incorporate driver mental and behavioral reaction under emergency conditions [10]. Lindell and Prater presented the principal behavioral variables affecting hurricane evacuation time estimates [11]. Pel et al. analyzed the impact of trip generation, departure rates, route flow rates, road capacities, and maximum speeds on evacuation by applying the macroscopic evacuation traffic simulation model EVAQ [12]. Pel et al. also reviewed travel behavior modeling in dynamic traffic simulations for evacuation [13].

In summary, some researchers on emergency evacuation have considered evacuee behavior under emergency conditions. However, the common issues in the above research are that they use only a deterministic set of parameters to represent realistic evacuee behavior, i.e. they view evacuee behavior as constant. They do not consider the impact of variation of evacuee behavior on evacuation clearance time. Therefore, new emergency evacuation management and control strategies from the perspective of evacuee behavior cannot be proposed. In this paper, we present impact of evacuees' destination choice and route choice behavior on evacuation clearance time by applying an artificial transportation system platform called TransWorld in a case study.

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II. Simulation Methodology

A. TransWorld

TransWorld is a state-of-the-art of artificial transportation system for modeling and computational experiments that was developed at the Complex Adaptive Systems for Transportation (CAST) Laboratory, Institute of Automation, Chinese Academy of Sciences. We used agent programming technology and object-oriented techniques to develop TransWorld, which can easily integrate human social behavior and traffic behavior. A generic individual behavior model in TransWorld is shown in Fig. 1. The features of TransWorld are: 1) it can grow artificial traffic behavior from bottom to up by using only population statistics and behavioral models, which is useful to test and validate transportation applications. 2) It provides a hierarchical multi-resolution traffic modeling and analysis from microscopic, mesoscopic, and macroscopic to logic emulations. 3) It is a computational experimental platform for the analysis and synthesis of transportation systems.

TransWorld is composed of network construction module, artificial population generator module, route planner module, microscopic traffic simulation module, computational results analysis module, two-dimensional and three-dimensional animation module, feedback module. TransWorld's system architecture and major components are shown in Fig. 2. Implementation details of TransWorld can be found in [14]. Other information on TransWorld can be found in [15] - [19].

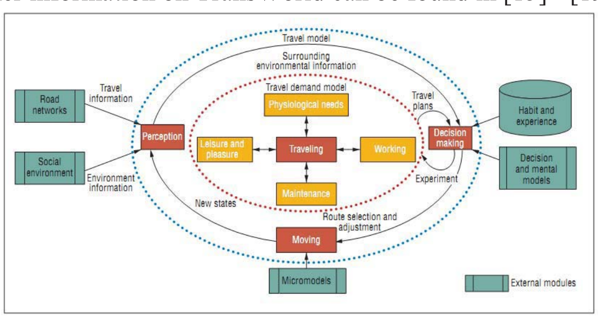


Fig.1. A generic individual behavior model in TransWorld

There is an activity type named "evacuation" in TransWorld to represent evacuee behavior. Each individual's activity is denoted as follows:

$$A_{ij}=(AT_{ij},D_{ij},ST_{ij},ET_{ij},P_{ij},M_{ij})$$

Where,

AT_{ij} : Activity type of individual i's j^{th} activity performed.

D_{ij} : Destination of individual i's j^{th} activity.

ST_{ij} : Start time of individual i's j^{th} activity.

ET_{ij} : End time individual i's j^{th} activity.

P_{ij} : Travel paths of individual i's j^{th} activity.

M_{ij} : Travel mode for individual i's j^{th} activity.

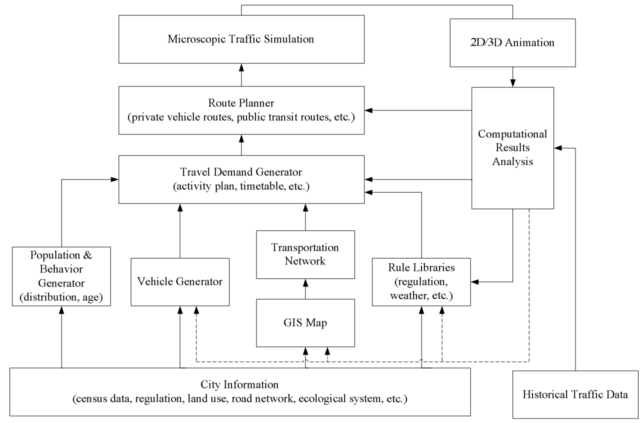


Fig.2. System architecture and major components of TransWorld

In order to study the impact of evacuees' different destination choice and route choice behavior on evacuation clearance time, we implemented well-recognized evacuees' destination choice and route choice behavior in TransWorld which are described in the following two sections.

B. Route Choice Mechanism

There are four commonly used route choice principles for emergency evacuation. They are: 1）Shortest Travel Distance (STD) Principle. Evacuees choose the shortest travel distance route to reach destinations. 2) Shortest Travel Time (STT) Principle. Evacuees choose the path with the shortest travel time to reach destinations. 3) Minimum Perceived Cost (MPC) Principle. Evacuees choose the path with the minimum perceived cost to reach destinations. 4) Evacuees can choose routes according to real time traffic information.

We need to solve the shortest path problem in order to implement STD, STT, and MPC principles in TransWorld. The Dijkstra algorithm and the Floyd algorithm are used to solve the shortest path problem. The Dijkstra algorithm can find the shortest path between one vertex and every other vertex, while the Floyd algorithm can find the shortest paths between all pairs of vertices. The Dijkstra algorithm and the Floyd algorithm are given as follows:

Given a directed weighted graph G with n vertices, let d_{ij} denote the distance between the vertex i and the vertex j, let $d_{ij}=\infty$ if there is no edge between the vertex i and the vertex j, and Let $W=[d_{ij}]$ denote the distance matrix for the graph G.

(1) The Dijkstra algorithm [20]

The basic concept of the Dijkstra algorithm is that: Assume $v_1 \to v_2 \to v_3 \to v_4$ is the shortest path between the vertex v_1 and the vertex v_4, then $v_1 \to v_2 \to v_3$ is the shortest path between the vertex v_1 and the vertex v_3 and $v_2 \to v_3 \to v_4$ is the shortest path between the vertex v_2 and the vertex v_4. Otherwise, if the shortest path between the vertex v_2 and the vertex v_4 is $v_2 \to v_* \to v_4$, the path $v_1 \to v_2 \to v_* \to v_4$ is shorter than $v_1 \to v_2 \to v_3 \to v_4$, which contradicts the previous assumption.

Let L_{si} denote the shortest distance between the vertex v_s and the vertex v_i. The Dijstra algorithm is as follows.

Step 1. Set $L_{ss} = 0$, and let the vertex s be labeled.

Step 2. Find the closest vertex neighboring to the vertex s, and let the vertex be noted as r. Compute $L_{sr} = L_{ss} + d_{sr}$, and put a label on the vertex r.

Step 3. Start from the labeled vertices; find the unlabeled vertices p neighboring to the labeled vertices. If $L_{sp} = \min\{L_{ss} + d_{sp}; L_{sr} + d_{rp}\}$, put a label on the vertex p.

Step 4. Repeat Step 3 until the target vertex t is labeled.

(2) The Floyd algorithm [21]

Let $W^{(0)} = W$, and construct matrix series $W^{(1)}, W^{(2)}, \cdots, W^{(n)}$. $d_{ij}^{(m)}$ in matrix $W^{(m)}$ denotes the distance from the vertex i to the vertex j. The matrix series are obtained based on $d_{ij}^{(m)} = \min\{d_{ij}^{(m-1)}, d_{im}^{(m-1)} + d_{mj}^{(m-1)}\}$. The Floyd algorithm is as follows.

Step 1. Construct the distance matrix $W = [d_{ij}]$ of the graph G and the auxiliary matrix $P = [p_{ij}]$, $i, j = 1, 2, \cdots n$, where

$$p_{ij} = \begin{cases} j, \ if \ d_{ij} \neq \infty \\ 0, \ if \ d_{ij} = \infty \end{cases}$$

Step 2. Set $k = 1$.

Step 3. Let $d_{ij} = d_{ik} + d_{kj}$ and $p_{ij} = p_{ik}$ for each i and j if $d_{ik} + d_{kj} < d_{ij}$.

Step 4. Set $k = k + 1$. If $k \le n$, go to Step 3; Otherwise, stop the algorithm.

C. *Destination Choice Mechanism*

There are two commonly used principles to describe evacuees' destination choice behavior. They are: 1) Evacuees choose the closest safe location as their destinations. 2) Evacuees choose a safe destination at random because of panic.

Choosing the closest safe destination needs to determine the shortest path. There are two solutions to find out the closest safe destination. One is to find out all the shortest distances from one origin O to all destinations first, then choose the destination with the minimum shortest distance. The other is to add a dummy vertex $D*$ first, and then connect D^* and all destination vertices with dummy links. All dummy links are assumed to have infinite capacity and zero cost. The closest safe destination can be found after computing the shortest path between O and D^*. The second solution is used in TransWorld.

III. COMPUTATIONAL EXPERIMENT DESIGN

A. *Test Bed Data*

The impact analysis of evacuees' destination choice and route choice behavior on evacuation clearance time is carried out in Zhongguancun area by using TransWorld. Zhongguancun area is located in Haidian District, Beijing, China. The selected area, which covers 15.3 km^2, west to Wanquanhe Road, east to Xueyuan Road and Xitucheng Road, north to North 4th Ring Road, and south to 3rd Ring Road, is a central business and educational district (see Fig. 3.). An artificial transportation system is constructed for the selected area using TransWorld, as shown in Fig.4. The area includes eighty two sites, which are directly related to traffic generation: twelve residential communities, twenty-eight office buildings, four schools, fifteen shopping malls, five recreational parks, three sport facilities, four restaurants and hotels, two hospitals, and nine shelters. The shelters are safe destinations for evacuees and located surrounding the area.

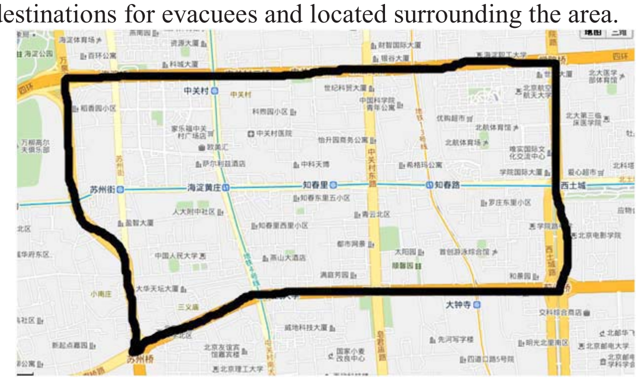


Fig.3. Location of Zhongguancun area

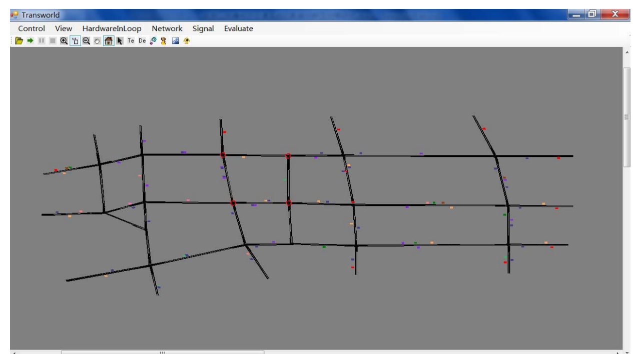


Fig.4. Artificial Transportation System for Zhongguancun area

B. *Experimental Design*

A hypothetical terrorist attack was assumed to happen in the selected area. People in this area need to be evacuated. We analyze the impact of evacuees' destination choice and route choice behavior on evacuation clearance time by doing computational experiments with TransWorld. The computational experiments conducted in this study follow the three basic principles of experimental design which are replication, randomization, and blocking. Evacuation clearance time is the performance measure in this study.

(1) Experimental conditions for the impact of destination choice on evacuation clearance time

The purpose of conducting experiments on the impact of destination choice on evacuation clearance time is to determine whether evacuees' destination choice behavior has an impact on evacuation clearance time or not, and if it has an impact how to choose destinations is the best.

In this experiment, thirty percentages of evacuees are assumed to have access to real time traffic information and they choose routes based on real time traffic information. Real time traffic information is updated every five minutes. Evacuees' departure time distribution is assumed to be normal distribution, $T \sim N(\mu, \sigma^2)$, where μ is 6:00, σ^2 is 0.5, and the minimum value of T is 5:45, the maximum value is 6:10. Assume that background traffic flow is generated based on Poison distribution for which the parameter is 0.02.

(2) Experimental conditions for the impact of route choice on evacuation clearance time

The purpose of conducting experiments on the impact of route choice on evacuation clearance time is to determine whether evacuees' route choice behavior has an impact on evacuation clearance time or not, and if it has an impact how to choose routes is the best.

In this experiment, real time traffic information is assumed to be updated every five minutes. Seventy percentages of evacuees are assumed to choose safe destinations at random, and thirty percentages of evacuees are assumed to choose destinations with minimum travel time. Evacuees' departure time distribution is assumed to be normal distribution, $T \sim N(\mu, \sigma^2)$, where μ is 6:00, σ^2 is 0.5, and the minimum value of T is 5:45, the maximum value is 6:10. Assume that background traffic flow is generated based on Poison distribution for which the parameter is 0.02.

IV. RESULTS AND DISCUSSION

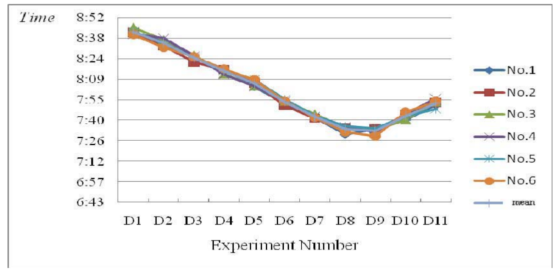
A. Impact of Destination Choice Behavior on Evacuation Clearance Time

The computational experiments on the impact of destination choice on evacuation clearance time is done by varying percentage of evacuees choosing destinations based on different principles while maintaining other inputs the same as described in section "*Experimental conditions for impact of destination choice on evacuation clearance time*". As stated in section "*Destination choice mechanism*", evacuees are assumed to choose destinations based on these two principles: 1) Evacuees choose the closest safe location as their destinations. 2) Evacuees choose a safe destination at random because of panic. The levels of these two destination choice principles are shown in Table 1.

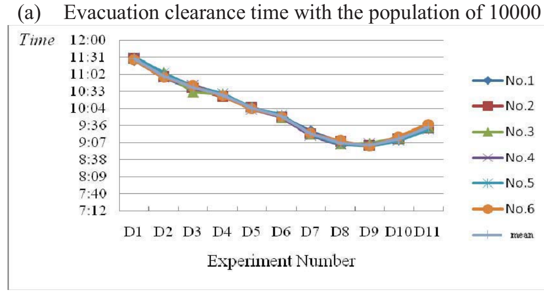
We ran each experiment six times with the population level of 10000, 20000, and 30000, respectively. Fig. 4 presents the impact of evacuees' destination choice behavior on evacuation clearance time.

Table 1 Levels of these two destination choice principles

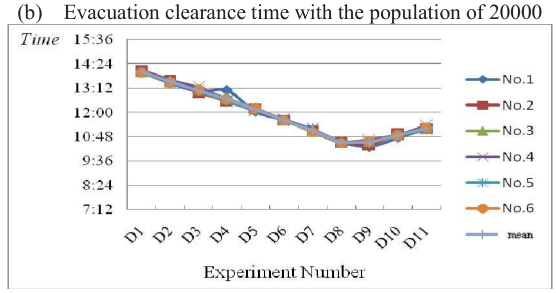
Destination Choice / Experiment No.	Random	Closest
Exp. D1	0%	100%
Exp. D2	10%	90%
Exp. D3	20%	80%
Exp. D4	30%	70%
Exp. D5	40%	60%
Exp. D6	50%	50%
Exp. D7	60%	40%
Exp. D8	70%	30%
Exp. D9	80%	20%
Exp. D10	90%	10%
Exp. D11	100%	0%



(a) Evacuation clearance time with the population of 10000



(b) Evacuation clearance time with the population of 20000



(c) Evacuation clearance time with the population of 30000

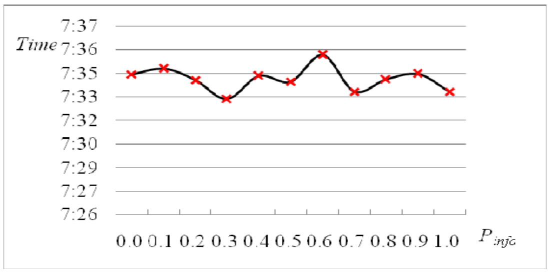
Fig.5. Impact of evacuees' destination choice behavior on evacuation clearance time

We can see that evacuees' destination choice behavior has a significant impact on evacuation clearance time from Fig. 5. Further, we conduct analysis of variance to computational experimental results (See Appendix for example), and conclude that: 1) evacuees' destination choice behavior has a highly significant impact on evacuation clearance time with the population of 10000, 20000, and 30000. 2) The evacuation clearance time is minimum with the destination choice principle combination Random-Closest that is 70%-30% or 80%-20%. The experimental results illustrate that evacuation managers need to adopt reasonable strategies to guide evacuees to choose destinations in practice, and it can significantly reduce evacuation clearance time.

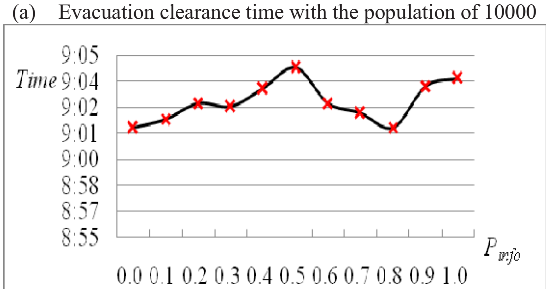
B. Impact of Route Choice Behavior on Evacuation Clearance Time

The computational experiments on the impact of route choice behavior on evacuation clearance time is done by varying percentage of evacuees having access to real time traffic information while maintaining other inputs the same as described in section "*Experimental conditions for impact of route choice on evacuation clearance time*". In this study, evacuees who can access to real time traffic information are assumed to choose shortest routes and change routes while en-route based on the traffic information updated every five minutes, and evacuees who cannot access to real time traffic information are assumed to choose shortest time routes and they have no ability to change route during evacuation. The levels of percentage of evacuees having access to real time traffic information, denoted as P_{info}, are 0%, 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90%, 100%.

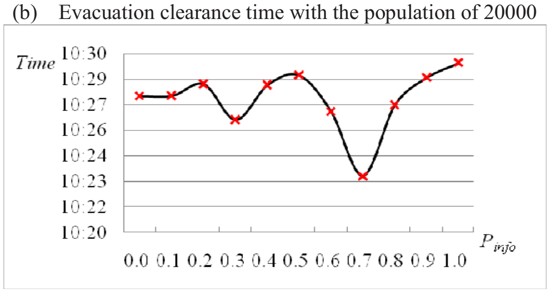
We ran each experiment six times with the population level of 10000, 20000, and 30000. Fig. 6 presents the impact of evacuees' route choice behavior on evacuation clearance time.



(a) Evacuation clearance time with the population of 10000



(b) Evacuation clearance time with the population of 20000



(c) Evacuation clearance time with the population of 30000

Fig.6. Impact of evacuees' route choice behavior on evacuation clearance time

We can see that evacuees' route choice behavior has some impact on evacuation clearance time from Fig. 5. However, we are not sure how significant it is. We need to conduct analysis of variance to computational experimental results to determine the significance. After conducting analysis of variance (See Appendix for example), we conclude that: 1) Evacuees' route choice behavior has no significant impact on evacuation clearance time with the population of 10000 and 20000. 2) Evacuees' route choice behavior has a significant impact on evacuation clearance time with the population of 30000, and the best value of P_{info} is 70%. The experimental results illustrate that evacuation managers need to adopt suitable strategy to guide evacuees to choose routes, and it can reduce evacuation clearance time.

V. Conclusions

In this paper, impact of evacuees' destination choice and route choice behavior on evacuation clearance time is studied. The impact analysis is done based on a case study by using TransWorld. Based on figures and analysis of covariance of computational results, we conclude that: 1) Evacuees' destination choice behavior has a highly significant impact on evacuation clearance time with the population of 10000, 20000, and 30000. And the best destination choice principle combinations are 70%-30% or 80%-20%. 2) Evacuees' route choice behavior has no significant impact on evacuation clearance time with the population of 10000 and 20000, while it has a significant impact on evacuation clearance time with the population of 30000, and the best value of P_{info} is 70%.

The computational experimental results illustrate that evacuation managers need to adopt reasonable strategy to guide evacuees' destination choice and route choices, and it can significantly reduce evacuation clearance time. The simulation methodology, computational results and discussion can be used to emergency evacuation planning. This study also provides potentials of new emergency evacuation management and control strategies from the perspective of evacuee behavior.

Acknowledgment

The author would like to express his sincere thanks to the anonymous referees for their valuable insights.

Appendix

Due to limitation of the paper length, we list part of results of computational experimental data summary and analysis of variance.

Table 2. Data summary of experiments on destination choice with the population number 30000

Group	Observation	Sum	Mean	Variance	95% confidence interval
D1	6	2 981.33	496.89	5.05	(494.527, 499.245)
D2	6	2 805.43	467.57	9.70	(464.30, 470.84)
D3	6	2 646.95	441.16	33.87	(435.05, 447.27)
D4	6	2 500.2	416.7	151.59	(403.78, 429.62)
D5	6	2 298.15	383.02	18.44	(378.52, 387.53)
D6	6	2 116.78	352.80	2.13	(351.267, 354.328)
D7	6	1 933.07	322.18	13.58	(318.31, 326.04)
D8	6	1 709.83	284.97	0.86	(283.996, 285.948)
D9	6	1 708.35	284.72	55.32	(276.92, 292.53)
D10	6	1 843.93	307.32	13.60	(303.45, 311.19)
D11	6	1 975.53	329.26	23.93	(324.12, 334.39)

Table 3. Analysis of variance of experimental data on destination choice with the population number 30000 ($\alpha = 0.05$)

Source	SS	df	MS	F	P-value	F crit
SSA	334091.9	10	33409.19	1120.135	9.23E-60	2.007792
SSE	1640.431	55	29.82602			
SST	335732.3	65				

Table 4. Data summary of experiments on route choice with the population number 30000

Group	Observation	Sum	Mean	Variance	95% confidence interval
0	6	1 699.95	283.32	13.28	(279.50, 287.15)
0.1	6	1 700.07	283.34	0.61	(282.527, 284.162)
0.2	6	1 704.02	284.00	2.63	(282.301, 285.705)
0.3	6	1 691.95	281.99	11.82	(278.38, 285.60)
0.4	6	1 703.75	283.96	12.18	(280.30, 287.62)
0.5	6	1 71	284.5	10.29	(281.13, 287.87)
0.6	6	1 694.7	282.45	4.087	(280.328, 284.572)
0.7	6	1 672.97	278.83	7.21	(276.01, 281.65)
0.8	6	1 696.93	282.82	3.81	(280.772, 284.872)
0.9	6	1 706.18	284.36	6.90	(281.61, 287.12)
1	6	1 711.17	285.19	6.31	(282.56, 287.83)

Table 5. Analysis of variance of experimental data on route choice with the population number 30000 ($\alpha = 0.05$)

Source	SS	df	MS	F	P-value	F crit
SSA	177.2645	10	17.72645	2.464465	0.016301	2.007792
SSE	395.6049	55	7.192816			
SST	572.8693	65				

Table 6. P-value for different P_{info} with the population number 30000 ($\alpha = 0.05$)

P_{info}	0%	10%	20%	30%	40%	50%	60%	80%	90%	100%
P-value	0.035	0.003	0.002	0.106	0.017	0.008	0.025	0.015	0.005	0.002

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