Predicting traffic flow evolution on degraded road networks

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Abstract

In order to investigate the influence of the forecast information provided by ATIS on the traffic flow evolution of the degraded road network, a weighted moving average based travel time forecasting method is designed, and the path update rule is established in the forecast information environment. The proposed route update rule is used to analyze the effects of prediction information dependency parameters, information quality parameters, weight parameters and network degradation degree on traffic flow evolution for a small test network. The results show that: 1) there is a threshold value for the dependence of travelers on the predicted information in the information environment, when the dependence is less than this value, the traffic flow quickly evolves to a stable state, and when the dependence is greater than this value, the network traffic flow will oscillate; 2) there is a situation where the higher the quality of the predicted information provided by the information system, the worse the traffic flow evolution; 3) for a particular degraded network, there is a certain optimal combination of weights that can be used to guide the release of forecast information of the network; 4) the smaller the degradation of the road network, the greater the role played by the forecast information.

1 Introduction

Advanced Traveler Information Systems (ATIS) can provide travelers with complete historical travel information as well as predicted time information, which is an important tool to regulate demand, balance network traffic distribution, and promote the full utilization of existing road network resources, thus improving the effectiveness of the transportation system [1–3]. The effectiveness of the transportation system can be improved [4–6]. It is widely believed that ATIS has an impact on travelers' choice of endpoints, modes and routes, inducing travelers to choose the most efficient endpoints, modes and routes [7–10]. Previous work considered the process of achieving user equilibrium state in ATIS environment and proposed a dynamic evolution model of traffic distribution flow under the influence of information by introducing the concept of decision

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travel cost, and also studied the day-by-day path selection behavior of travelers and the evolution law of network traffic flow under the effect of prediction information [11–15].

With the widespread construction of rail transit and urban express arterial roads, the degradation of the actual urban road network will exist for a long time, and it is of great practical significance to study and grasp the influence of the prediction information provided by ATIS on the dynamic evolution of the degraded road network [16–20]. In this study, a weighted moving average based path travel time prediction method is designed to simulate the individual traveler's path selection behavior for a randomly degraded road network using MATLAB, and to analyze the influence of the prediction information on the traveler's selection behavior and the network traffic flow evolution pattern.

2 Path travel time under degraded road network

Consider the network $G = (N, A)$, where N is the set of nodes and A is the set of road segments. Let W be the set of OD pairs, R_w denote the set of paths between OD pairs w, and use Dw to denote the demand of OD pairs w. Use C_a to denote the actual capacity of road section a. When the road network is degraded, the capacity of the road section and the travel time of the road section are random variables. Assume that the upper limit of the capacity of road section a is its design capacity c_a^d, and the lower limit is $\theta_a c_a^d$, where θ_a $(0 \leq \theta_a \leq 1)$ is the section capacity degradation factor, and further assume that C_a obeys the uniform distribution on the interval of $[\theta_a c_a^d, c_a^d]$. In order to obtain the path travel time under the degraded road network, the BPR function is chosen as the road section characteristic function in this study:

$$T_a\left(x_a, C_a\right) = t_a^0\left[1 + \alpha\left(x_a/C_a\right)^\beta\right], \forall a \in A \tag{1}$$

where: α, β for the parameters of the BPR function; x_a indicates the flow rate on section a; t_a^0, T_a are the free flow travel time of section a and the travel time when the flow rate is x_a, respectively.

Assume that the random variation of the roadway capacity C_a and the traffic volume x_a on the roadway do not affect each other. Then, under the assumption of uniformly distributed roadway capacity, the mean value of roadway travel time can be expressed as:

$$E\left(T_a\right) = t_a^0 + \alpha t_a^0 x_a^\beta \frac{\left(1 - \theta_a^{1-\beta}\right)}{\left(c_a^d\right)^\beta\left(1 - \theta_a\right)\left(1 - \beta\right)}, \forall a \in A \tag{2}$$

Assuming that the section travel times are independent of each other, the route travel times can be obtained by adding up the section travel times:

$$S_{rw} = \sum_a T_a \delta_{ar}^w, \forall w \in W, r \in R_w \tag{3}$$

where: S_{rw} is the travel time on path r between OD pairs w; δ_{ar}^{w} is the roadway path association variable, which takes the value of 1 when path r between OD pairs w passes through roadway a, otherwise it takes the value of 0.

When the section travel times are independent of each other, regardless of the distribution they obey, the path travel times always obey a normal distribution according to the central limit theorem, as long as the Lindbergh condition is satisfied. Therefore, the mean value of path travel time can be obtained as:

$$E\left(S_{rw}\right) = \sum_{a}\left\{\delta_{ar}^{w}\cdot\left[t_a^0+\alpha t_a^0 x_a^{\beta}\frac{\left(1-\theta_a^{1-\beta}\right)}{\left(c_a^d\right)^{\beta}\left(1-\theta_a\right)\left(1-\beta\right)}\right]\right\}, \quad \forall w\in W, r\in R_w \tag{4}$$

3 Traffic flow evolution model with prediction information

In the capacity degradation road network, it is assumed that when travelers choose a route, the main consideration is the perceived route travel time, and the traveler's perception of the route travel time comes from the prediction information provided by the information system.

In the predictive information environment, the perceived travel time of traveler i on day $(t+1)$ for path r between OD pairs w is denoted as:

$$\mathrm{H}_{rw}^{i,t+1}=\mathrm{T}_{rw}^{i,t+1}+\varepsilon_{rw}^{i,t+1}, \forall r\in \mathrm{R}_{W}, \mathrm{w}\in \mathrm{W} \tag{5}$$

where: $T_{rw}^{i,t+1}$ is the expectation of $H_{rw}^{i,t+1}$, $\epsilon_{rw}^{i,t+1}$ is the random error.

Suppose $\epsilon_{rw}^{i,t+1}$ is an independent identically Gumbel distributed random variable with zero expectation, then, according to discrete choice theory, the probability that traveler i between OD pairs w chooses path r on day $(t+1)$ in the predicted information environment is:

$$p_{rw}^{i,t+1}=\frac{\exp\left(-\lambda\tau_{rw}^{i,t+1}\right)}{\sum_{k\in R_w}\exp\left(-\lambda_{kw}^{i,t+1}\right)}, \forall r\in R_w, w\in W \tag{6}$$

where: λ is given by the information induced system, which indicates the randomness of the path selection behavior of travelers in the predicted information environment, and can be interpreted as the quality of the information, the larger λ indicates the higher quality of the received information and the more accurate information provided by the ATIS device.

From the above equation, we can see that the path selection probability is related to the expectation of path perception time, and the following will develop an update model of path perception time expectation for the travelers in the prediction information environment.

Since advanced travel information systems can provide historical travel information for all paths of travelers and predicted travel information for each path on the current day. In this study, it is assumed that the expected perceived time of traveler i in the information environment for path r between OD pair w on day $(t+1)$ is the weighted average of the predicted travel time of path r on day $(t+1)$ and the expected perceived time of that path on day t, i.e:

$$\mathrm{T}_{rw}^{i,t+1} = \gamma\mu_{rw}^{t+1} + (1-\mathrm{y})\mathrm{T}_{rw}^{i,t}, \forall r \in \mathrm{R_W}, \mathrm{w} \in \mathrm{W} \tag{7}$$

where: γ is the parameter of the traveler's dependence on the predicted information; μ_{rw}^{t+1} denotes the predicted travel time of path r between OD pairs w on day $(t+1)$, which is published by the information system.In this study, μ_{rw}^{t+1} takes the weighted moving average of the actual average time of the path in the previous 3 days, i.e.:

$$\mu_{rw}^{t+1} = \frac{V_t E\left(S_{rw}^{t}\right) + V_{t-1} E\left(S_{rw}^{t-1}\right) + V_{t-2} E\left(S_{ww}^{t-2}\right)}{V_t + V_{t-1} + V_{t-2}} \tag{8}$$

where: V_t, V_{t-1} and V_{t-2} denote the influence weights of the actual average travel time of the route on day t, day $(t-1)$ and day $(t-2)$, respectively, whose values directly affect the evolution process of traffic flow and thus the effect of information dissemination.

4 Case Studies

The test road network is a grid network includes 12 road sections and 9 nodes. the parameters of the BPR function are taken as $\alpha = 0.15$, $\beta = 4$, and the OD demand is assumed to be $D_{1,9} = 500$, and the capacity degradation factor of each road section is taken as 0.8. the free flow time and design capacity of each road section are given in Table 1.

Due to the lack of historical experience of travelers, the path expectation perception time was initialized to the free flow time for the first three days, and updated with Eqs. (7) and (8) from the fourth day. There are six paths between the OD pairs (1-9) in the test network, so in order to save space, only path 1 (node number 1-4-7-8-9, hereinafter referred to as path 1) is analyzed in this study.

4.1 The effect of information-dependent parameter γ on the evolution of traffic flow

In the simulation experiment, the perceptual parameter is taken as $\gamma = 0.3$, and the corresponding static random user equilibrium flow on path 1 is easily obtained as 105.6 pcu/h. The weight parameters V_t, V_{t-1} and V_{t-2} are taken as 5, 3 and 2, and the number of simulation days is taken as 500 d. The effect of the parameter γ on the evolution of traffic flow in the information environment is investigated with the same values of the previous parameters. The mean and

Table 1: Free flow travel time and design capacity of each link

Road	t_a^0/min	c_a^d/(pcu/h)
1	20	360
2	12	360
3	15	240
4	12	180
5	12	360
6	10	150
7	12	180
8	15	240
9	10	150
10	30	360
11	15	240
12	15	240

standard deviation of the traffic flow on path 1 for the last 50 days and its trend when γ varies from 0.01 to 0.9 are given in Table 2.

Table 2: Mean and standard deviation of the last 50 days' flow on route 1 with different parameter

γ	Average	Std. Dev.	γ	Average	Std. Dev.
0.01	105.8	9.6	0.5	118.7	93
0.1	105.6	9.7	0.6	114.6	164.8
0.2	106.6	12.1	0.7	110	163.4
0.3	107	10.2	0.8	107.7	196.4
0.4	107.3	15.5	0.9	119.5	214.8

From Table 2, we can see that there is a critical value of $\gamma \approx 0.4$ in the test network, when $\gamma \leq 0.4$, the path update rule can make the system evolve to a static stochastic user equilibrium state; however, when $\gamma > 0.4$, the standard deviation of the traffic of path 1 increases sharply, indicating that the system oscillates at this time, which mainly originates from the travelers' over-reliance on and compliance with the path selection provided by the induced system. This is mainly because travelers rely too much on the path travel time information provided by the induced system, which leads to the frequent path switching and the instability of the path traffic.

4.2 Influence of information quality parameter γ on the evolution of traffic flow

According to the previous analysis, there exists a critical value of $\gamma \approx 0.4$ for the test network when the information quality parameter $\lambda = 0.3$. In this study, we fix the predicted information dependence degree parameter as $\gamma = 0.5$ and study the effect of the information quality parameter λ on the evolution of path 1 traffic with the other parameters taking the same values. The statistical results of the traffic evolution on path 1 when the parameter λ is varied from 0.01 to 0.3 are given in Table 3, and the static random user equilibrium traffic for path 1 with different information quality parameters λ are shown in Table 3.

Table 3: Statistical results of the flow evolution on route 1 with different parameter λ ($\gamma = 0.5$) pcu/h

λ	Statistics	1–50	51–100	101–150	151–200	201–250	251–300
0.01	Average	85	85.2	87.4	86.9	84.3	86.9
	Std. Dev.	9	8.8	8.6	9.24	8.7	7.9
0.05	Average	95	95.3	94.3	93.1	95.5	94.4
	Std. Dev.	10	8.3	8.3	7.6	10	6.5
0.1	Average	100	99.9	99	99.4	99.9	99.5
	Std. Dev.	22	11.6	9.3	8.7	8.5	7.3
0.2	Average	106	105	104	104	105	104
	Std. Dev.	53	12.6	9.4	12.2	11	11.4
0.3	Average	109	116	121	117	116	125
	Std. Dev.	98	125	80	137	65.3	104

According to Table 3, when λ is 0.01, 0.05, 0.1 and 0.2, the traffic flow on path 1 evolves quickly to the corresponding static random user equilibrium flow; however, when λ is taken as 0.3, the flow on path 1 oscillates and always deviates from the static random user equilibrium state, which indicates that there is a situation when the information dependence parameter exceeds a critical value and the information system This indicates that when the information dependence parameter exceeds a critical value, the higher the quality of the prediction information provided by the information system, the worse the effect of traffic flow evolution.

4.3 Determination of the optimal weighted moving average combination of weights

The determination of the optimal combination of weights for the weighted moving average is studied with the other parameters taking the same values. Firstly, the impact weights of the actual average travel time on the path on day $(t-2)$ are fixed as 0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9 and 1. Then the impact weights on day (t-1) and day (t) are set randomly, and a total of 66 sets of data are obtained by removing the duplicate weight combinations. In this study, the

Table 4: Statistical results of the flow evolution on route 1 with different parameter λ ($\gamma = 0.5$) pcu/h

Combination	Statistics	Parameter γ 0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
(8, 2, 0)	Average	20.6	105.8	105.7	107.4	113.5	117.9	100.2	100	118.3	120	120
	Std. Dev.	3.7	7.7	10.9	13.4	162	151.6	202	202	212.6	215.5	215.7
(7, 2, 1)	Average	20.7	105.6	106.7	106.8	109.8	116.4	105.5	100.6	119.4	119.6	119.9
	Std. Dev.	4.8	9.7	8.9	10.1	151.5	178	199.4	201.7	214.6	215	215.6
(6, 3, 1)	Average	20.8	106.3	106.7	107.1	110.7	103.9	121.9	100.7	100.5	119.9	119.3
	Std. Dev.	4.2	9.9	10.2	10	23.8	132.6	174.2	201.3	201.7	215.6	214.5
(6, 2, 2)	Average	22.12	107	106.2	106.5	113.3	102.2	98.1	97.7	128.3	119.9	119.9
	Std. Dev.	4.2	11.51	10.3	13.7	123.9	188.4	196.9	197.1	218.7	215.4	215.6
(5, 3, 2)	Average	19.9	105.7	105.7	106.3	108	121.1	124.1	110.7	106.7	120	119
	Std. Dev.	4	10.5	10.1	10.1	16.2	97.1	176.7	171	196.2	215.2	213.7
(5, 2, 3)	Average	20.9	105.5	106.3	105.6	112.7	123.2	114	129.5	118.5	119.7	120
	Std. Dev.	5.1	8.7	11.7	13.9	82.6	162.7	179.7	191.7	203.1	215.2	215.7
(5, 1, 4)	Average	21.3	106.2	106.8	108.4	117.4	111.2	106	116.9	97.7	134.6	120.1
	Std. Dev.	4.6	11.5	10.4	32.7	159.2	188.1	188.2	191.3	181	218.6	215.7
(4, 1, 5)	Average	21.1	106.6	105.6	108.4	109	83.5	91.1	101.3	113.6	127.3	120
	Std. Dev.	4.2	8.2	11.7	66.5	114.4	183.6	193.5	201.2	184.2	203	215.6
(3, 1, 6)	Average	21.7	105.4	101.5	103.6	112.5	103.5	104.3	104.9	100.5	99.6	130.1
	Std. Dev.	4.9	8.3	70.5	122.2	157	150	165.8	199.3	201.8	200.5	221.5
(2, 1, 7)	Average	20.1	107	102.5	93.7	108.5	125	119.3	128.4	105.3	121.5	104.6
	Std. Dev.	4.3	9.3	91.3	107.3	151	186.4	185.8	198.4	199.4	195.7	199.7
(1, 1, 8)	Average	20.8	108.1	107.2	106	123.6	139.3	122	170	169	168	167.4
	Std. Dev.	4.6	12.9	180.2	132.7	183.7	222.6	199.5	228.6	237.9	236.4	227.2
(1, 0, 9)	Average	20.8	117.4	105.7	95.5	117.3	114.4	113	108.9	158.2	109.3	13
	Std. Dev.	4.5	161.6	187	191.8	208.8	205.4	171.9	173.5	204.2	187.3	13.1
(0, 0, 1)	Average	20.8	116.4	107.7	94.3	96.8	113.1	108.3	101.8	155.5	108.9	12.8
	Std. Dev.	4.5	163.2	189.5	191.8	193.9	205.3	182.5	176.1	201.4	187.3	12.8

mean and standard deviation of the flow on path 1 in the last 50 days with the information dependence parameter γ are given in 13 sets of weight combination scenarios, and the statistical results are shown in Table 5. The variation of the mean and standard deviation of the flow on path 1 in the last 50 days with the combination of weights and the information dependence parameter γ are presented in Figs. 3 and 4, respectively.

According to Table 4, it can be seen that: 1) when the combination of weights is (1,1,8), (1,0,9) and (0,0,1), the test network is in equilibrium only when γ is taken as 0. When γ is taken as greater than 0, the traffic of path 1 oscillates and the network never reaches equilibrium; 2) when the parameter γ is taken as 0.1 and 0.2, the evolution results of the combination of weights (3,1,6), (2, 1,7) show that the mean value of flow does not fluctuate greatly in both γ cases, but the standard deviation changes abruptly and the system starts to oscillate; 3) When the parameter γ is 0.2 and 0.3, the evolution of the weight combinations (5,1,4) and (4,1,5) show that the mean value of flow increases in both γ cases, the standard deviation changes abruptly and the system is in an unstable state; 4) When the parameter γ is 0.3 and 0.4, the mean value of flow increases in both γ cases and the standard deviation changes abruptly and the system is in an unstable state; 5) When the parameter γ is 0.3 and 0.4, the mean value of flow increases in both γ cases and the standard deviation changes abruptly. (8,2,0), (7,2,1), (6,2,2), (5,2,3), and (6,3,1), the test network oscillates and the system is in an unstable state, but the evolution of the weight combination (5,3,2) shows that the network is in a stable state; 5) When the parameter γ is varied in the interval (0.4,1], When the parameter γ varies in the interval of (0.4,1], the test network oscillates under various combinations of weights, and the system always deviates from the steady state. The traffic flow evolution results under the combination of weights (5,3,2) are better, and the information system can improve the quality of the prediction information and maximize the operational efficiency of the road network when the travelers rely on the prediction information to a higher degree ($\gamma \leq 0.4$) under this combination of weights.

5 Conclusions

1. The information dependence parameter γ has an important influence on the stability of the network traffic flow evolution and there is a certain threshold value ($\gamma = 0.4$), below which the system can evolve to a static stochastic user equilibrium state relatively quickly, and once it is exceeded, the travelers are overly dependent on information and lack of inertial opinion, which will lead to system oscillations.

2. Once the information dependence parameter exceeds the critical value ($\gamma > 0.4$), the better the information quality ($\lambda \geq 0.3$), the more oscillations occur in the evolution of network traffic flow and always deviate from the equilibrium state; on the contrary, the worse the information quality,

the better the evolution of network traffic flow, which can provide a basis for the reasonable determination of information quality parameters in the information guidance system.

3. The combination of weights of the weighted moving average in the path update rule has a significant impact on the stability of the network traffic flow evolution, and there is an optimal combination of weights (5,3,2) for the actual network in this study.

4. When the capacity degradation of the network is more serious ($\theta \leq 0.3$), the network traffic flow cannot evolve to a stable state under various information-dependent parameters, and as the capacity degradation of the network decreases, the information-dependent parameters that can ensure the stable evolution of the network traffic flow show an increasing trend, indicating that the smaller the capacity degradation of the network, the greater the role of predictive information.

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