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Procedia Engineering 16 (2011) 79 – 87
Procedia Engineering
www.elsevier.com/locate/procedia

International Workshop on Automobile, Power and Energy Engineering

The study of a new method of driving cycles construction

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Abstract: Thinking about the traffic process of vehicle,the change of speech over time is an uncertain variable, the driving cycle of vehicle is studied by the Markov theory in random process , By analysis and calculating a number of experimental data, the transition probability matrix of original data was obtained by maximum likelihood estimation to determine the statistical characteristics of the experimental data， then according the constraints of the transfer matrix, a large number of model events were selected from experimental datas randomly to develop a driving cycle. On the theoretical basis of the above, the actual application analysis was carried out with a example of typical roads driving cycles in Hefei, and define 12 characteristic parameters to evaluate the constructed cycle. The results showed that this method is more representative than the traditional method.

Key words: Driving cycle;Markov; Maximum likelihood estimation ;Random number

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Introduction

Vehicle driving cycle VDC (namely vehicle testing cycle) is aseries of data points representing the speed of a vehicle versus time, which is used to value the capability. Whether it can reflect the real working condition of a vehicle or engine under specific traffic condition concerns reasonable evaluation of the economic function and emission function of the vehicle or engine. Reasonable evaluation and precise test of the economic function and emission function of the vehicle or engine, in turn, affects whether we can give the vehicle and engine economical efficiency and emission a reasonable and effective majorization. The driving cycle around the world can be divided into USDC, EDC, JDC. At present, we are using European emission test cycle, and this standard is greatly different from the vehicle

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doi:10.1016/j.proeng.2011.08.1055

working condition in cities in China. Therefore, it is of great importance to carry on a investigation of big and middle-size cities in china[1]. As a matter of fact, in countries advanced in auto industry, there are also a lot of real cycle systems, eous systems, for example, Andre from France got the average city steering working condition[2]; Swede Eva Ericssion analyzed factors that affects steering behavior [3]; based on the stochastic process theory, Debbie A. and Niemeier analyzed and established the driving cycle of California, America[4]. China started the research in driving cycle a little late, but a lot of scholars are researching driving cycle in recent years, and their methods are traditional methods based on Microtrips. Such as, Ma zhixiong who researched vehicle driving cycle with the method of dynamic clustering[5]; Shi shuming who researched the driving cycle of Changchun city with principal component analysis; Ai guohe who investigated probability of using principal component analysis on data process in vehicle driving cycle[7]. Based on the Markov theory of stochastic process theory, the state transition probability matrix of the test datas was fixed by calculation and analysis of a large number of typical test datas in Hefei, and as a constraint, a driving cycle was established by selecting some typical fragments from the large number of test datas.

1. Basic theory of markov

The relationship of speed - time at any time in driving process is uncertain, so actually driving cycle should be a random process。By take non-independence tests on each state, we concluded that the driving cycle can be regarded as a fixed and discrete markov process [8].

Construction on the ground of random process is a new method , it divides driving cycles into a series of model events by markov theory. According to the character of markov process, each model event is not independent. Whether the current model events happen or not does only relate with a prior model event. For model events which have slight change in velocity, markov process can keep the driving characteristics unchanged. With maximum likelihood estimation method (MLE), we can divide the original data into the representative modal events. The advantage of using this partitioning algorithm is that it defines modal events by the speed and acceleration profile itself and thus maintains the integrity of the modal event.

We denote the observed time o as n and each of the observed data points (acceleration/deceleration rate) as a_i, $i=1,2,3,\dots n$。 Meanwhile, We also denote $\bar{a}$ the vector of n observations a_i, and $\bar{\theta}$ the corresponding vector of parameters. Under the assumptions of multivariate normality and equal covariance, we can define likelihood function as following:

$$L(\bar{\theta}|\bar{a})=\prod_{g=1}^{G}(\pi_g^{n_g}\sigma_g^{-n_g})\exp\left\{-\frac{1}{2}\sum_{g=1}^{G}\sum_{C_g}\frac{(a_i-\mu_g)^2}{\sigma_g^2}\right\} \quad (1)$$

Where： G——the number of clusters， $g=1,2,3\dots G$；

C_g——the collection of observed data whose acceleration belongs to cluster g；

n_g——the number of observed points in C_g ；

π_g——the probability of the acceleration a_i in cluster g $\left(\sum_g \pi_g = 1\right)$；

μ_g——average value of observed points in cluster g ；

σ_g——variance of observed points in cluster g ；

According to the partition methods above, we can divide original data into four clusters(i.e., acceleration cluster, deceleration cluster, idle cluster and cruise cluster) and call them modal events. Then use maximum likelihood estimation to divide the modal events which have similar average speed and similar acceleration feature into modal events set. Each modal events set is defined as state S of markov chain, all the model events set state make up markov space. According to markov process, we can get the transition probability among each state, which is the probability of state *j* occurring given the current state *i*. then we can form matrix:

$$P_{k\times k}=\begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1k} \\ p_{21} & p_{22} & \cdots & p_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ p_{k1} & p_{k2} & \cdots & p_{kk} \end{bmatrix}_{k\times k} \qquad (2)$$

For a fixed markov process, we can use likelihood function defined as following to calculate the transition probability[9]

$$p_{ij}=\frac{N_{ij}}{\sum_{s} N_{ij}} \qquad (3)$$

Where N_{ij} is the number of events which state i transfers to state j (at time $\tau-1$.)

2. Data partition basis and determination of characteristic parameters

Driving cycles is a course of speed varies, its main parameters(e.g. the average speed, idle running time etc .) should be consistent with the actual local traffic conditions, or as close as possible. To get the driving cycle, we must have many data of speed variance. According to a certain standard mathematics method, we extract representative driving cycles from the original data. There are several concepts used in the processes of data partition by markov: idle mode, acceleration mode, deceleration mode and cruise mode. This paper defines four modals as following:

(1) idle mode: the speed is 0, but the engine is still at work ,
(2) acceleration mode: vehicle speed change value is positive, and acceleration absolute value is greater than 0.1 m/s^2,
(3) deceleration mode: vehicle speed change value is negative, and acceleration absolute value is greater than 0.1 m/s^2 absolute;
(4) cruise mode: the acceleration absolute value is less than(or equal to) 0.1 m/s2 and speed is not 0.

To be convenient for evaluating the constructed driving cycle, We measure the performance of a driving cycle by comparing 12 parameters that describe driving characteristics, , including average speed v_m, average driving speed v_{mr} , speed standard deviation v_{sd} ,average acceleration a, maximum acceleration a_{max}, minimum acceleration a_{min}, acceleration standard deviation a_{sd}, idle time proportion P_i, acceleration time proportion P_a, deceleration time proportion P_d, cruise time proportion P_c, average road power *p*. average road power is considered with the rolling resistance, friction, air resistance and accelerate resistance and its function shows as follows [4] :

$$p=\left(86.3V_t+0.0459V_t^{\,3}+317(V_t-V_{t-1})V_t\right)/1000 \quad (V_t>V_{t-1})$$

$$p=\left(86.3V_t+0.0459V_t^{\,3}\right)/1000 \quad (V_t\le V_{t-1}) \qquad (4)$$

where V_t is the instantaneous speed at time *t*.

3. The analysis of examples and application

3.1 Experiment data collection

Considering the road traffic characteristics, driving time, vehicle conditions, the driver behavior, environmental factors, we chose 5 typical roads (e.g.shengli road, tunxi road etc.) in hefei for sampling. Each section will be sampled 14 days on end, including Saturday and Sunday. The sampling time covered everyday peak hours, flat peak periods and low peak periods. This study chooses cars for object owning to its larger numbers. Followed the fixed route and traffic flow, the driver should keep a certain distance, don't overtake forcibly. The collected speed, acceleration and speed - acceleration joint frequency distribution are shown in figure 1,2, and 3 below.

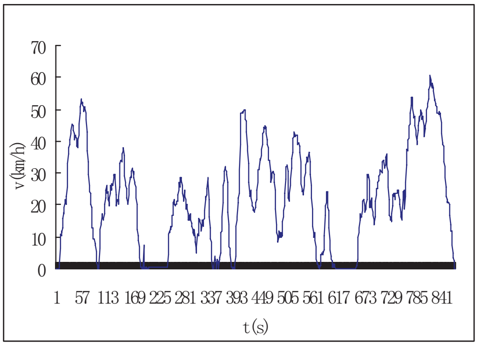


Fig 1 Test speed-time curves of representative roads

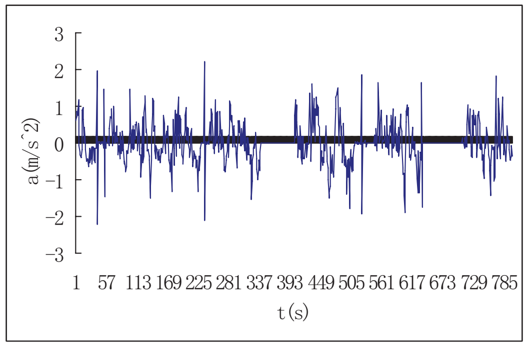


Fig 2 Test acceleration-time curves of representative roads

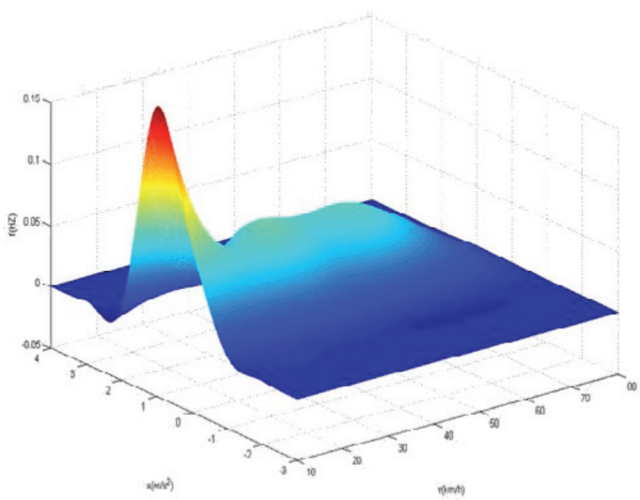


Fig 3 Joint probability distributions of test speed- acceleration

3.2 Data processing

According to the theoretical knowledge from the first part, using a maximum likelihood estimation method firstly, we divide experiment data into modal events that vary with time, forming 4 clusters (i.e. idle cluster, cruise cluster, acceleration cluster and deceleration cluster) shown in chart 4. Reuse a maximum likelihood estimation method and make modal event which has similar average speed and acceleration together to state shown in figure 5, as shown in the state, forming the state space for $S=\{1,2,3,\cdots 20\}$, the value of each state characteristic parameters is shown in table 1, the dimension is listed above.

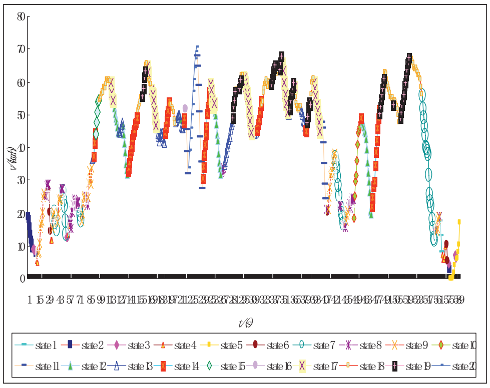


Fig 4 Cluster partition result of the MLE for the speed-time curve

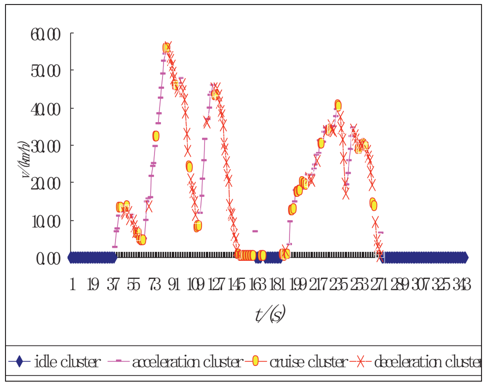


Fig 5 States partition result of the MLE for the speed-time curve

Tab.1 Twenty-state parameters of experiment data

	v_{min} (km/h)	v_{max} (km/h)	v_m (km/h)	a_{min} (m/s^2)	a_{max} (m/s^2)	a (m/s^2)
State 1	0.11	31.69	9.97	-2.20	1.02	-1.11
State 2	0.11	28.94	8.35	-2.20	1.98	-0.36
State 3	0	16.54	2.27	-2.07	2.2	0.005
⋮	⋮	⋮	⋮	⋮	⋮	⋮
State 18	49.15	75.33	58.49	-0.61	0.58	-0.003
State 19	43.06	73.95	57.68	-1.12	1.59	0.27
State 20	33.76	70.51	55.01	-0.16	1.47	0.86

3.3 Calculation of transition probability matrix

Take the typical road driving cycle in Hefei as an example, based on maximum likelihood estimation, we divided the original data into 6543 modal according to the changes of acceleration. Then modal events with similar average speed and acceleration forms 20 sets of modal events by reusing maximum likelihood estimation, i.e.20 states. By several partition tests, the criteria for the classification in Table2 is the most reasonable.(unit of speed (km / h), acceleration units (m/s^2) . The transition frequency (N_{ij}) of different state is shown in Table 3.

Tab 2 The partition standard of state

	a≤*-0.8*	*-0.8*<a≤*-0.1*	*-0.1*<a≤*0.1*	*0.1*<a≤*0.8*	a>*0.8*
$0 \le v_m < 15$	state1	state 2	state 3	state 4	state 5
$15 \le v_m < 35$	state 6	state 7	state 8	state 9	state 10
$35 \le v_m < 50$	state 11	state 12	state 13	state 14	state 15
$v_m \ge 50$	state 16	state 17	state 18	state 19	state 20

Tab 3 Modal event transfer frequencies of different states

State	1	2	3	…	18	19	20	*sum*
1	3	11	23	…	0	0	0	67
2	7	149	120	…	0	0	0	454
3	2	79	495	…	0	0	0	785
⋮	⋮	⋮	⋮	⋱	⋮	⋮	⋮	⋮
18	0	0	0	…	114	77	0	323
19	0	0	0	…	98	163	0	353
20	0	0	0	…	2	0	0	2

According to the transfer frequencies of modal events in table2， we can get the transition probability matrix as follows（unit %）：

$$P_{20\times 20}=\begin{bmatrix} 4.48 & 16.42 & 34.33 & \cdots & 0 & 0 & 0 \\ 1.54 & 32.82 & 26.43 & \cdots & 0 & 0 & 0 \\ 0.25 & 10.06 & 63.06 & \cdots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 35.29 & 23.84 & 0 \\ 0 & 0 & 0 & \cdots & 27.76 & 46.18 & 0 \\ 0 & 0 & 0 & \cdots & 100 & 0 & 0 \end{bmatrix}_{20\times 20} \quad (5)$$

3.4 Construction of the candidate driving cycle

To build a reasonable candidate cycle, we conduct according to the following steps

1）the selection of the initial segment

According to formula (6) , compared the frequency between each line initial segment and the entire data collection , we select the segment which has minimum Δ and is close to the test data between 60s and120s, as the initial segment of the candidate cycle [12].

$$\Delta = \sum (P_{v,a} - p_{v,a})^2 \quad (6)$$

Where $P_{v,a}$ means the frequency of speed is v and acceleration is a; $p_{v,a}$ means the frequency of the selected segment.

2) Extend the length of cycle

Once the initial segment is determined, the state of the last event can be determined. Take this model as the initial state, according to transition probability matrix, we choose state whose transition probability is the largest from the initial state as the state of next modal event. Since a state contains a lot of modal events in experiment data, so after the state of extended model is determined, we should select a modal event from the state to extend the candidate cycle. We choose the random selection method. In order to ensure the randomness, we use computer models to achieve random selection of events , the specific implementations are shown in Figure 6. With the method, we extend the candidate cycle one by one until it reaches the desired length.

3) Constructing process needs to pay attention to two issues

a. According to equation 6, once the next even chosen, the frequency deviation between the newly synthesized driving cycle and the experiment data should be convergent gradually.

b. After selection of the candidate cycle, in order to make the candidate cycle and the state transition probability matrix of data samples come from the same distribution, it is necessary to take two independent samples Kolmogorov-Smirov (K-S) test on the line transition probability of all states. Select them whose average two-tailed similarity level at K-S are greater than or equal to 0.95 as the final candidate cycle.

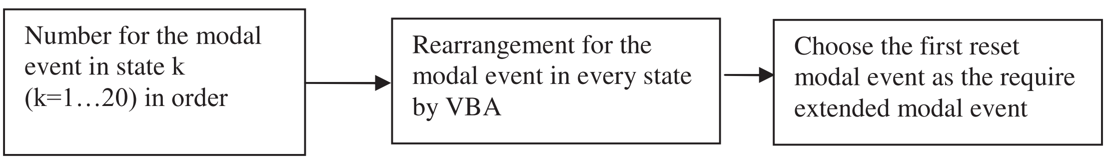


Fig 6 The flow chart of random selection model event

3.5 select representative cycle

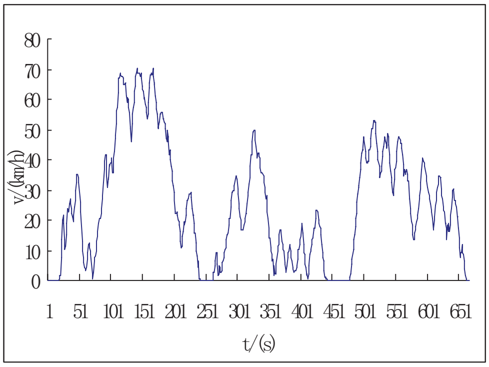
In order to select the representative and suitable cycle from the candidate cycles, 12 characteristic parameters which have been defined above are regarded as the evaluation of the twelve criteria. Then we defined the PM as the error-weighted value of characteristic parameters between the candidate cycle and experiment data. The cycle that had the minimum value(*PM*) is selected as the ultimate driving cycles , the expression of PM shows as follows [12]:

$$\begin{aligned} PM = {} & w_1|\Delta v_m| + w_2|\Delta v_{mr}| + w_3|\Delta a| + w_4|\Delta P| + w_5|\Delta a_{\max}| \\ & + w_6|\Delta a_{\min}| + w_7|\Delta P_i| + w_8|\Delta P_a| + w_9|\Delta P_d| + w_{10}|\Delta P_c| \\ & + w_{11}|\Delta v_{sd}| + w_{12}|\Delta a_{sd}| \end{aligned} \tag{7}$$

4. result analysis

Where Δ equals the error between the candidate cycle and the experiment data, w_i (i = 1,2 ... 12) represents the weighted value of the characteristic parameters, namely the importance in evaluate process. For convenience, All the weighted values are defined as 1.

By this analysis, we construct the representative cycle according to random number and draw a joint probability distributions of the error between test and representative cycle, shown in Figure 7 to Figure 10, while the use of traditional methods (Principal component analysis and clustering techniques) to build the driving conditions, and they were compared in Table 4.



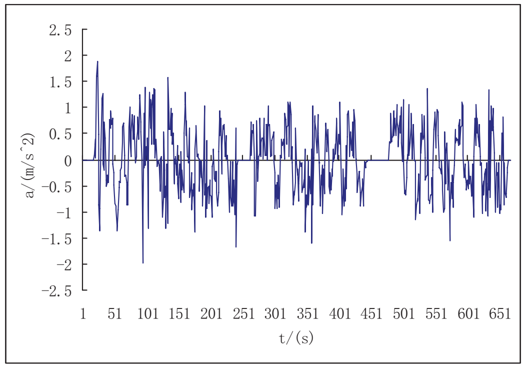
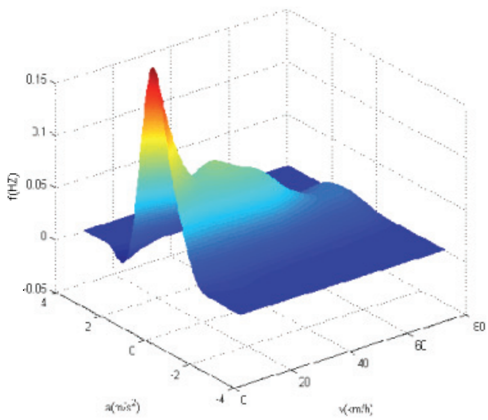
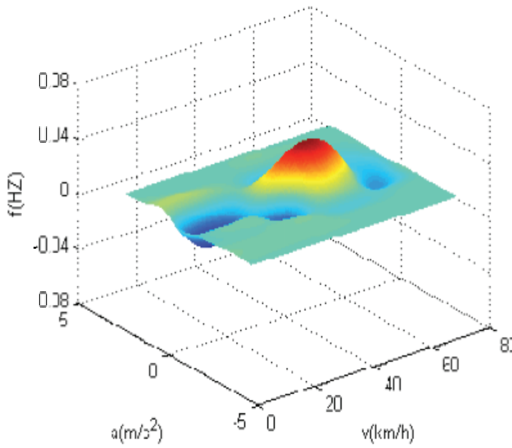


Fig 7 Speed-time curves of representative cycle

Fig 8 Acceleration -time curves of representative





cycle

Fig 9 Joint probability distributions of representative cycle speed- acceleration

Fig 10 Joint probability distributions of the distinction between test and representative cycle

Tab 4 Comparation of parameters between the experiment data and the driving cycle

Parameters	test data	new methods	traditional methods
v_m (km/h)	25.27	24.98	28.87
v_{mr} (km/h)	28.27	28.28	25.48
v_{sd} (km/h)	24.51	24.59	21.18
a (m/s^2)	0	0	-1
a_{max} (m/s^2)	2.20	1.89	2.42
a_{min} (m/s^2)	-2.27	-1.99	-1.71
a_{sd} (m/s^2)	0.575	0.602	0.52
p (kw)	2.17	2.16	2.20
p_i (%)	12.02	11.89	11.71

p_a (%)	33.75	34.48	34.86
p_d (%)	35.79	36.64	35.71
p_c (%)	18.44	16.99	17.72

Through Figure 10 and Table 4, we can see the error frequency between the representative cycle and experiment data is less than $\pm$ 0.02, the average relative error between the random number method and the experiment data is 3.88%, while the error between the traditional method and the experiment data is 16.92% . Therefore, Markov methods is able to represent the actual driving cycle of typical roads, and better than traditional methods.

5. Conclusion

(1) This paper presents the new method for constructing driving cycles based on random process theory. Compared with the traditional method, it is no longer based on short trip, it is by the Markov process that obtained transition matrix of experiment data and determine the statistical characteristics.

(2)After the statistical characteristics of the experiment data determined, we select modal events randomly from experiment data to extend the length of driving cycles with the restraint of transition probability matrix ,until reach the desired length .

(3)In the process of using maximum likelihood estimation for the state partition, in addition to the speed factor considered, we take the acceleration factors into account, makes the modal events more detailed. The results show that this partition is more scientific, reasonable and construction based on it is more representative.

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