CHAPTER IV

NUMERICAL INVESTIGATION USING COMPUTER SIMULATION

4.1 General

The numerical investigation of axle load identification of a passing vehicle on a bridge using the two previously mentioned methods is considered in this section. A vehicle moving on a single span simply supported bridge with constant speed is simulated using the formulation previously explained in chapter III. Besides the consideration of a vehicle as moving dynamic multi-degree of freedoms system, the two-axle vehicle model with 4 degrees of freedom is also considered. The comparison of identification approaches for effectiveness and accuracy evaluation is carried out and discussed. Influences of various parameters such as sampling frequency, structural discretization, moving vehicle speed, bridge surface roughness, number and position of response measurements, measurement noise level, axle spacing of vehicle, axle weight distribution, error of measurement and random vary parameters simulation are considered. Based on extensive numerical examples, the identification accuracy, robustness and reliability of the considered identification methods can be systematically investigated. In addition, the results obtained from this chapter will be used as the guidance for both small-scale and full-scale investigations as well as for the improvement of load identification toward real B-WIM application.

4.2 Vehicle-Bridge Interaction Responses Simulation

In this section, the vehicle is assumed to have two axles and crosses the simply supported bridge with a constant speed. The bending moment histories of a bridge at various sections subjected to a passage of the vehicle are simulated from the vehicle-bridge interaction model as defined in Eq. (3.50). To minimize the simulation error, the Newmark's β method with a fine time interval of 0.001 second is adopted to numerically determine the bridge bending moments at considered sections. Based on these obtained moment responses, the axle load of the passing vehicle is identified using either Method I or Method II. The axle load identifications from the two methods are extensively investigated and the obtained results are compared under various conditions of vehicle-bridge parameters. To quantify the identification accuracy of the two methods, the axle weight estimation errors for the front axle, rear axle and gross weights are, respectively, defined in Eq. (3.88)

It is noted that the weighting matrices, **B**, defined in Eq. (3.55) for Method I and Eq. (3.74) for Method II are both set to identical matrix to prevent the bias comparison. It is also noted that the regularization parameter, λ, as required by Eq. (3.74) for Method II is simply set to 1.0.

The parameters for the vehicle-bridge system are listed in Table 4.1. The assumed vehicle axle loads are simulated from the vehicle model in which the vehicle properties are measured from the real truck (Mulcahy, 1983). The bridge structure is modeled as a simply supported beam having span length of 10 m. Its properties are approximated from a real concrete bridge in Thailand. It is noted that the first five natural frequencies of this bridge are computed to be 6.7, 26.8, 60.2, 107.1 and 167.3 Hz. The vehicle having gross weight of 250 kN is considered. Its dynamic properties are obtained from model identification by testing of a real two-axle 10-wheel truck.

Table 4.1 Vehicle-bridge system parameters

Bridge	Vehicle		
L = 10 m	I_v = 4.87 kgm^2	m_1 = 500 kg	m_2 = 700 kg
EI = 1.96x10^9 Nm^2	m_v = 23800 kg	K_{s1} = 9.50x10^6 N/m	K_{s2} = 16.98x10^6 N/m
ρA = 10.8 kg/m	S = 4.65 m	K_{t1} = 5.38x10^6 N/m	K_{t2} = 12.82x10^6 N/m
ξ = 0.02 for all mode	a_1 = 0.811	C_{s1} = 4.0x10^4 N/m/s	C_{s2} = 4.0x10^4 N/m/s
	a_2 = 0.189	C_{t1} = 4.0x10^4 N/m/s	C_{t2} = 4.0x10^4 N/m/s

Figure 4.1 shows the typical bending moment histories of the bridge under a passage of the vehicle with a speed of 15 m/s at $L/3$, $L/2$ and $2L/3$, respectively. Using these simulated bridge moment responses as the input, the axle loads of the vehicle can be identified by Methods I and II as outlined in previous section and are shown in Figure 4.2, respectively. It should be noted that Method I yields directly the two axle weights of the vehicle, while Method II firstly yields the time-varying magnitudes of axle loads which, consequently, can be averaged to estimate the corresponding axle weights of the vehicle. The figures clearly reveal that both methods can accurately estimate the front and rear axle weights of the vehicle. In this particular case, the

estimation errors of the front axle, rear axle and gross weights, respectively, about 3.9, 4.4 and 4.3 from the Method I and about 2.9, 3.7 and 3.5 from Method II are obtained.

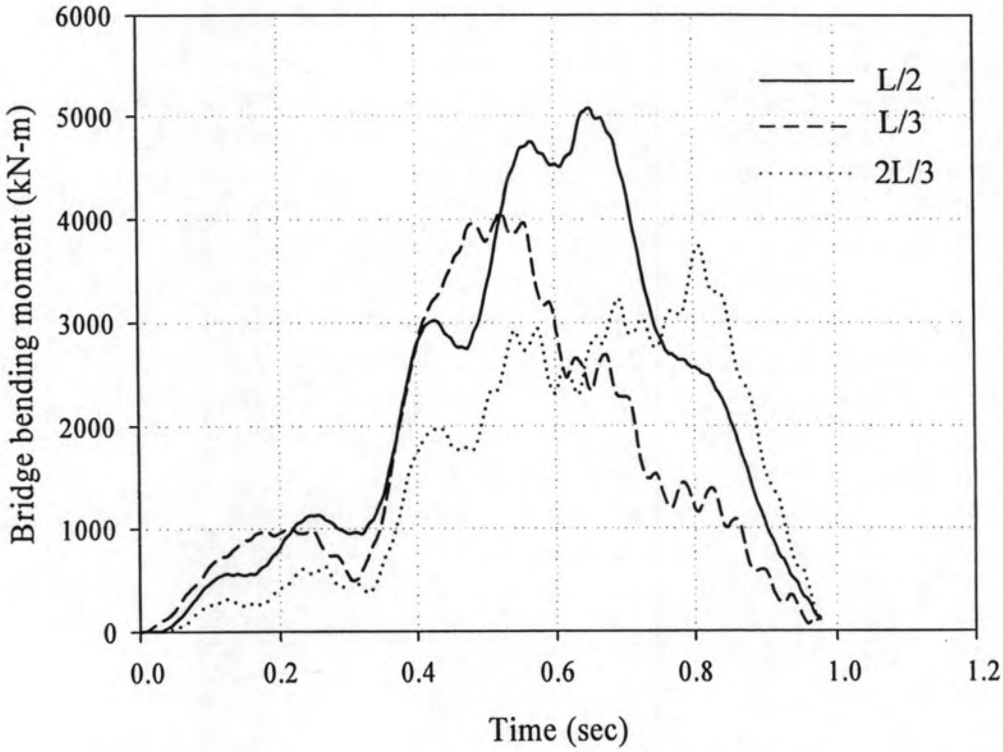
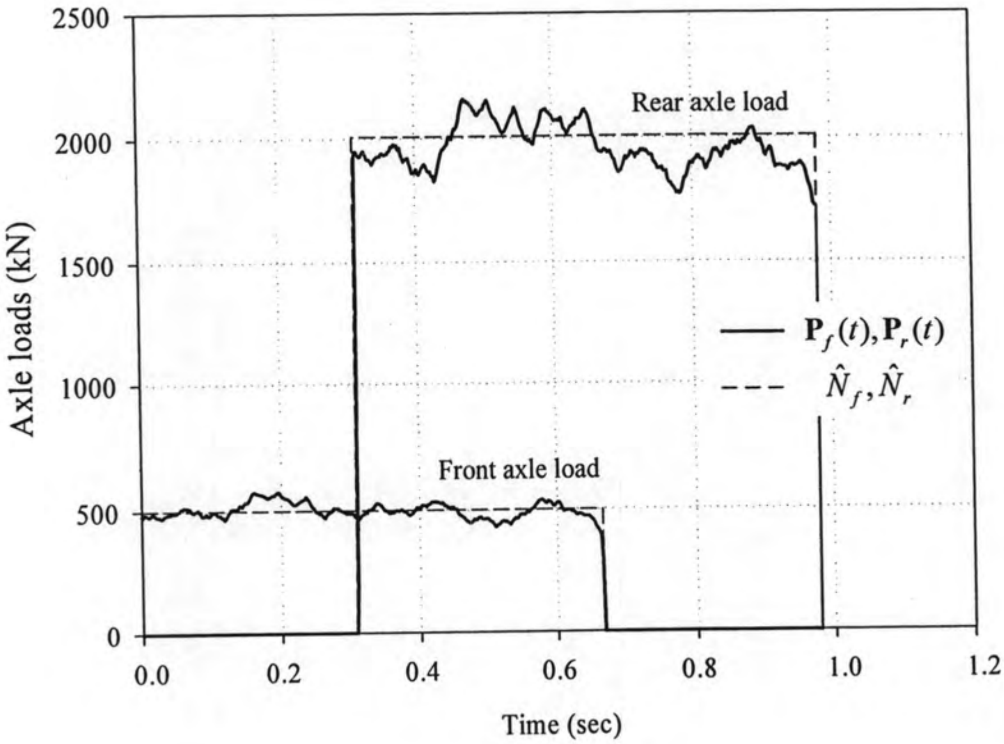
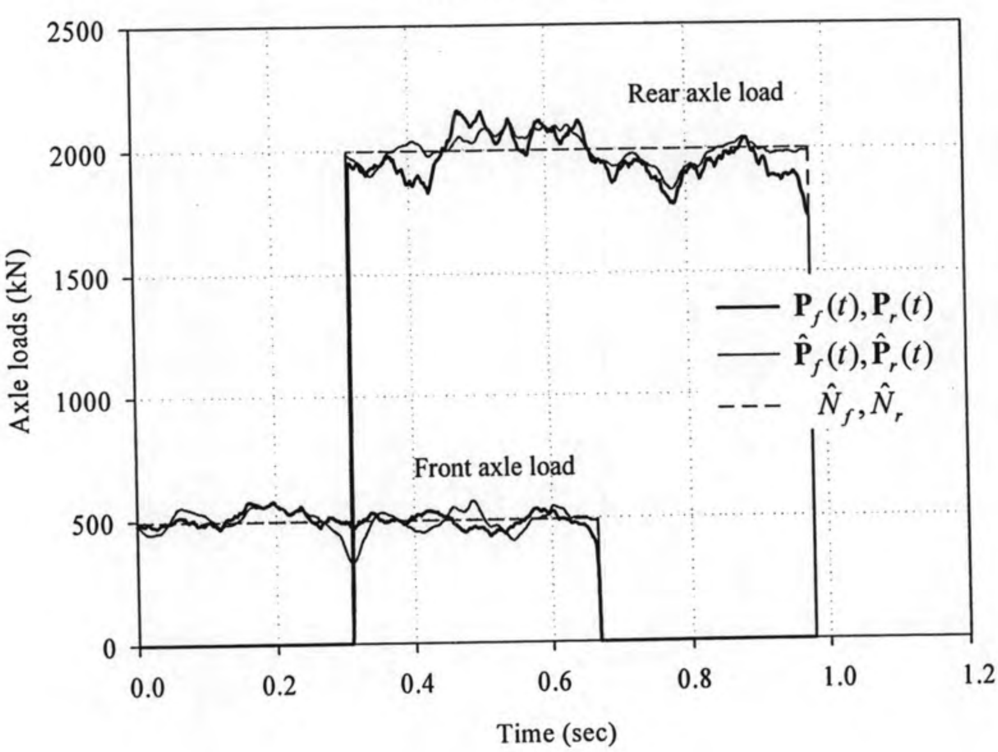


Figure 4.1 Typical bending moment histories of the bridge under a passage of the vehicle with a speed of 15 m/s and roughness surface of level 3



(a) Method I



(b) Method II

Figure 4.2 Actual axle loads and corresponding axle weight estimations (a) using Method I (b) using Method II

4.3 Effects of Various Parameters on Axle Load Identification

In this section, the effects of various parameters on axle load identification methods are studied. The three groups of parameters consist of measurement parameters, modeling parameters and physical parameters. The effects of measurement parameters such as number and location of sensors, measurement noise level and sampling frequency of data acquisition system are firstly considered. Once the effects of measurement parameters are understood, the proper measurement parameters for the loads identification are suggested. Then the modeling parameters and physical parameters are investigated.

4.3.1 Effects of Bridge Discretization and Sampling Frequency

The effects of bridge discretization and sampling frequency on the accuracy of the axle load identification methods are considered. The vehicle with gross weight 250 kN moving on the bridge at a constant speed of 30 m/s under various bridge discretization refinements and various sampling frequencies of the bridge bending moments are simulated. Based on the obtained bridge bending moments at three sections, i.e. $L/3$, $L/2$ and $2L/3$, the axle loads of the vehicle are identified using Method I and Method II. Table 4.2 lists the estimation errors of front axle, rear axle and gross weights of the vehicle from the two methods. In the table, the simulated bending moments of the bridge are sampled with the sampling frequency varied from 20 – 1,000 Hz. To estimate the axle weights of the vehicle using Method II, the bridge structure is discretized into 4, 8, 12 and 16 beam elements. It should be noted that the bridge discretization for Method I is not essential since the method utilizes the continuous influence line function. In the table, the bridge surface roughness of level 2, which induces the dynamic in the axle loads around 10%, is also assumed.

Employing Method II, it is obviously found from the table that the accuracy of the axle weight estimations is not affected by discretization refinement of bridge structure if it is discretized by more than 4 elements. The table also indicates that the accuracy of the axle weight estimations by the two methods is significantly influenced by the sampling frequency. The axle weight estimation errors become larger when the sampling frequency is smaller. However, it is noticed that the axle weight estimation errors obtained from both methods are rather constant if the sampling frequency is faster than around 50 Hz. Therefore, throughout this numerical study, the number of bridge elements is set to 8 while the sampling frequency is fixed at 500 Hz to guarantee the highest accuracy of the identification methods. This implies that the bridge vibrations up to the 6th natural mode are taken into account. It is noted that these settings are used only for the axle load identification methods. The vehicle-bridge interaction simulation of Eq. (3.50) still employs a very fine time interval of 0.001 second (1000Hz) with 16 beam elements to accurately simulate the actual bending moments of the bridge under a passage of the vehicle.

Since Method II provides not only the estimated axle weight of the vehicle but also its dynamic axle loads, it is therefore interesting to investigate the accuracy of the identified dynamic axle loads of the method. To do so, the load identification errors of front and rear axle defined in Eq. (3.86) are listed in Table 4.3 under different sampling rate and number of beam elements. Similar to the axle weight estimation, it is observed from the table that the load identification error is not affected by discretization refinement of bridge structure if it is discretized by more than 4 elements. The sampling frequency is significantly affected to the axle load identification errors which become larger when the sampling frequency is smaller. However, in this numerical study, the bridge discretization with 8 elements and the sampling frequency with 500 Hz provide the high accuracy of axle load identification Method II.

Table 4.2 Percentage errors of the axle weight estimations for different sampling rates and number of beam elements

Sampling frequency (Hz)	Method I			Method II											
				Number of beam elements											
				4			8			12			16		
	front	rear	gross	front	rear	gross	front	rear	gross	front	rear	gross	front	rear	gross
20	-7.4	12.2	8.3	8.8	13.9	12.9	8.7	12.6	11.8	6.5	12.4	11.2	5.8	12.3	11.0
30	-9.5	12.1	7.8	-4.8	8.9	6.2	-0.3	8.1	6.4	1.7	8.0	6.7	2.7	7.8	6.8
40	-10.0	12.4	7.9	-0.9	7.0	5.4	-7.2	10.3	6.8	-6.6	11.0	7.4	-5.9	11.0	7.7
50	-10.3	12.6	8.0	-0.3	6.3	5.0	0.4	7.8	6.3	0.6	8.8	7.1	0.6	9.0	7.3
100	-10.3	12.6	8.0	-4.6	7.2	4.9	-2.9	8.9	6.5	-3.1	9.7	7.2	-2.8	9.9	7.4
200	-10.0	12.5	8.0	-7.9	9.4	5.9	-4.9	9.5	6.6	-3.6	9.8	7.1	-3.6	10.2	7.4
300	-10.1	12.5	8.0	-7.3	9.1	5.9	-4.9	9.5	6.6	-3.7	9.7	7.0	-3.7	10.1	7.3
400	-10.0	12.5	8.0	-7.8	9.5	6.0	-4.7	9.4	6.6	-3.6	9.7	7.0	-3.1	9.8	7.2
500	-10.1	12.5	8.0	-7.8	9.5	6.0	-4.6	9.4	6.6	-3.6	9.7	7.0	-3.1	9.8	7.2
1000	-10.1	12.5	8.0	-7.7	9.4	6.0	-4.5	9.3	6.6	-3.6	9.6	7.0	-3.0	9.7	7.2

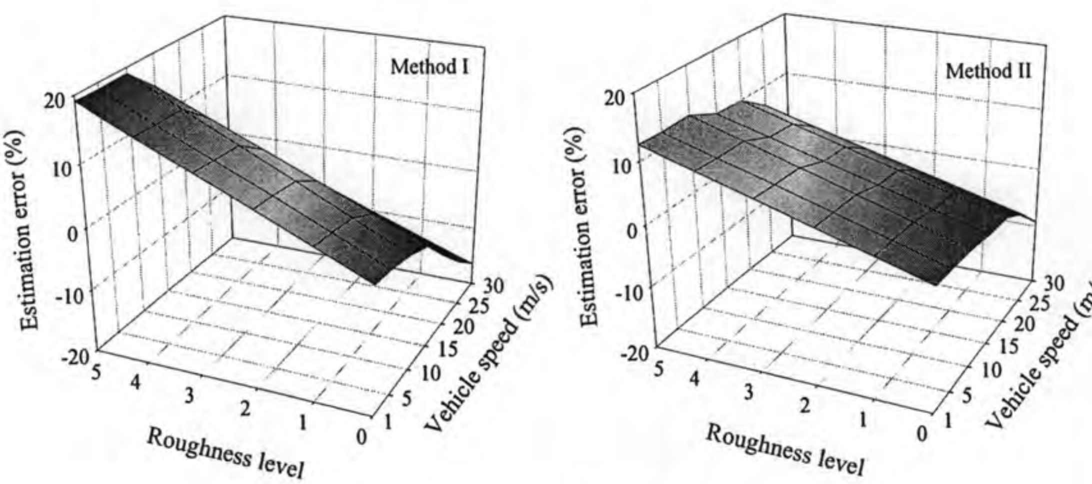
Table 4.3 Relative percentage errors of the axle load identification for different sampling rates and number of beam elements

Sampling frequency (Hz)	Method II							
	Number of beam elements							
	4		8		12		16	
	front	rear	front	rear	front	rear	front	rear
20	26.3	45.9	27.9	45.2	27.1	45.0	27.0	44.9
30	-23.4	33.9	-27.5	33.5	-27.2	33.5	-26.9	33.4
40	-22.9	28.7	-27.5	30.2	-27.0	30.5	-26.2	30.5
50	-21.2	25.6	-22.3	25.9	-22.9	26.3	-23.8	26.4
100	-21.2	19.1	-21.6	19.6	-21.4	19.8	-21.3	19.9
200	-23.1	13.2	-22.4	12.8	-21.6	12.8	-21.4	12.9
300	-23.1	13.1	-22.5	12.9	-21.6	12.8	-21.5	13.0
400	-23.4	11.0	-22.5	10.5	-21.7	10.4	-21.3	10.3
500	-23.4	11.5	-22.5	11.0	-21.6	10.9	-21.3	10.9
1000	-23.5	9.3	-22.7	8.7	-21.8	8.6	-21.5	8.5

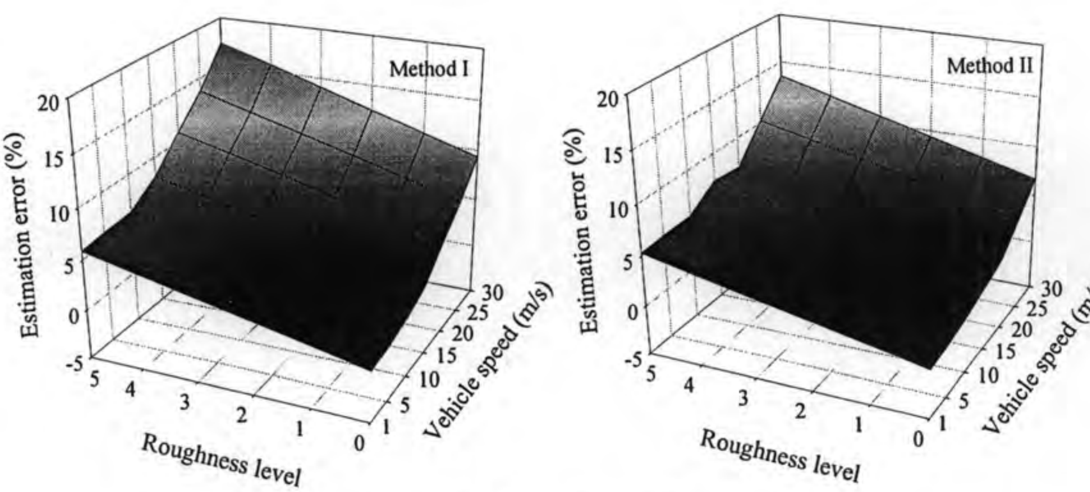
4.3.2 Effects of Vehicle Speed and Bridge Surface Roughness

The effects of vehicle speed and bridge surface roughness on the accuracy of the weight estimation methods are investigated. The practical range of vehicle speed from 1 to 30 m/s is considered. The magnitude of the bridge surface roughness, $|r(x)|$, is varied and is classified into 6 roughness levels ranging from 0 (smooth surface) to 5 (very rough surface) according to the obtained dynamic characteristic of the simulated axle loads. In general, the roughness levels of 0, 1, 2, 3, 4 and 5 indicate the averaged dynamic participations in each axle loads of the vehicle moving at 15 m/s around 0%, 5%, 10%, 15%, 20% and 25%, respectively. The vehicle moving on the bridge having different roughness levels at various speeds is simulated. Based on the obtained bridge moments at three sections, i.e. $L/3$, $L/2$ and $2L/3$, the axle weights of the vehicle are estimated using Method I and Method II. Figures 4.3(a) to 4.3(c) plot the estimation errors of front axle, rear axle and gross weights of the vehicle from the two methods under various vehicle speeds and bridge roughness levels. For a better visualization, the weight estimation errors from Method I and Method II are separately plotted and shown in the left and right figures, respectively. These figures reveal that the weight estimation errors from both methods exhibit similar characteristic under variations of vehicle speed and bridge roughness levels. It is found that their estimation errors tend to increase as the roughness level increases due to larger fluctuation of axle loads. Although the faster vehicle speed also induces larger fluctuation of axle loads, the speed effects on the estimation errors for the front (Figure 4.3(a)) and rear axles (Figure 4.3(b)) become different. The former becomes smaller while the latter becomes larger when the vehicle speed increases. Since the rear axle is much heavier than the front axle, the estimation errors of the gross weight from both methods (Figure 4.3(c)) are almost the same as those of the rear axle (Figure 4.3(b)). Comparing the errors from the two estimation methods, it is found from these figures that Method II is superior for all considered ranges of vehicle speeds and roughness levels. In particular, the estimation errors of the front axle, rear axle and gross weights using Method II are, respectively, varied from -9.26% to 12.53%, -0.20% to 13.51% and -0.27% to 11.30% and using Method I are, respectively, varied from -16.38% to 19.20%, 0.02% to 17.31% and 0.01% to 13.71%. It is observed from the Figure 4.3(c) that the estimation errors of the gross weight of the vehicle from the two methods can be, however, controlled to be within ±10% if the surface roughness is kept below level 4, regardless of the vehicle speed.

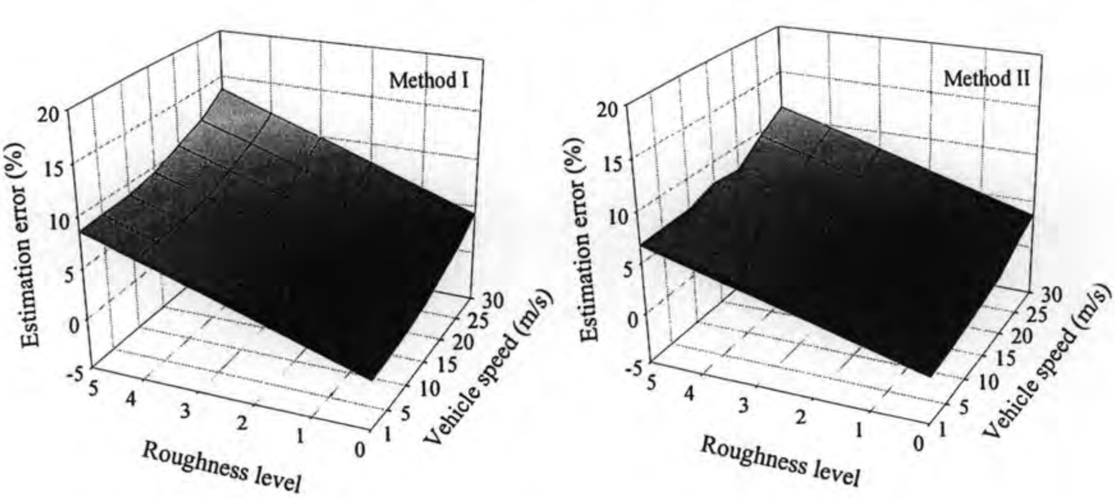
Regarding to the identified dynamic axle loads resulting from Method II, the dynamic load identification errors of front and rear axle defined in Eq. (3.86) are plotted in Figure 4.4 under various vehicle speeds and bridge roughness levels. It is noticed from the figure that the load identification error is affected by both vehicle speed and bridge roughness level. The error increases as the vehicle speed or the bridge roughness level increases. Based on considered ranges of speeds and roughness levels, the identification errors of -23.11% to 16.05% for the dynamic front axle and -0.55% to 13.49% for the dynamic rear axle are observed.



(a) Front axle weight

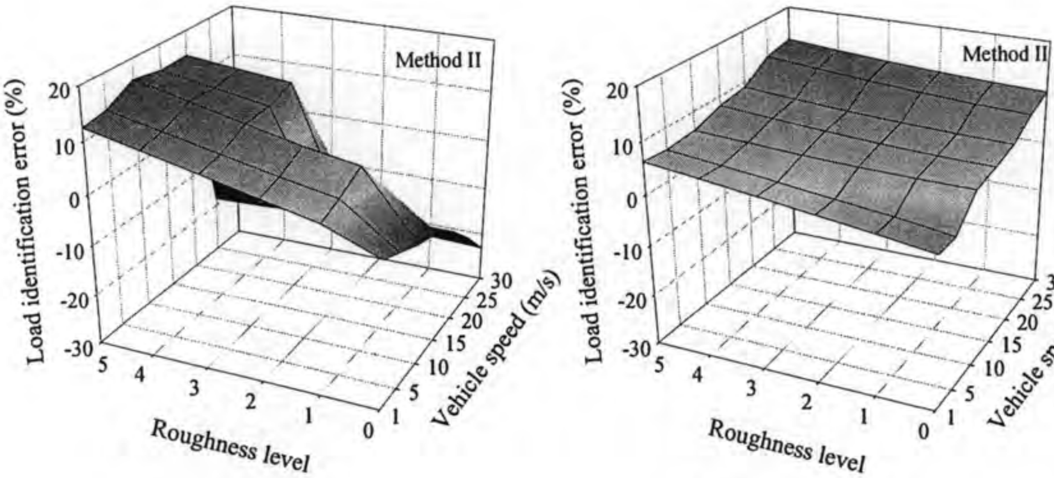


(b) Rear axle weight



(c) Gross weight

Figure 4.3 Estimation errors of the axle weights under various roughness levels and vehicle speeds for (a) front axle weight (b) rear axle weight and (c) gross weight



(a) Front axle load (b) Rear axle load

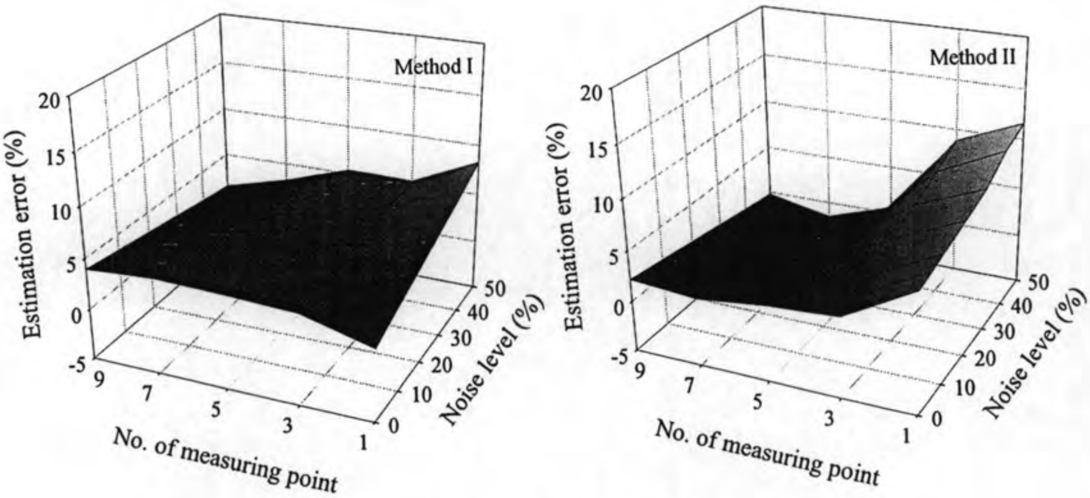
Figure 4.4 Identification errors of the axle loads of Method II under various roughness levels and vehicle speeds for (a) front axle load (b) rear axle load

4.3.3 Effects of Number of Measuring Sections and Noise Level

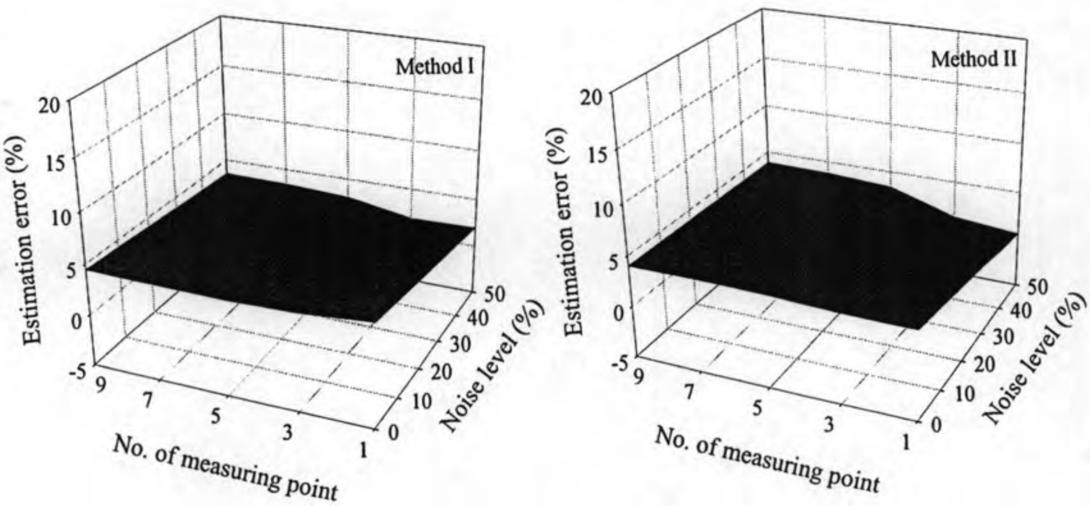
The influences of number of measuring sections and noise levels in the input signals on the weight estimation accuracy resulting from the two methods are investigated. The vehicle moving at a constant speed of 15 m/s on the bridge having the roughness of level 3 is simulated. Based on the obtained bridge moments at various section arrangements as in Table 4.4, the axle weights of the vehicle are estimated using Method I and Method II. It is noted that the number of the measuring sections of 1, 3, 5, 7 or 9 is considered. To study the noise effect, the obtained moment signals at all sections are assumed to be polluted with 5% to 50% white noise. Figures 4.5(a) to 4.5(c) show the estimation errors of the front axle, rear axle, and gross weights of the vehicle from the two methods under various number of measuring sections and noise levels. The results indicate that influences of number of measuring sections and noise levels on the weight estimation accuracy resulting from the two methods are very small, especially for the rear axle and gross weights. Although both estimation methods are expected to be very robust against noise effect since their computations inherently contain time averaging procedure. The significant effect of noise on the weight estimation of the front axle is observed when small number of measuring sections, i.e. 1 or 3, is employed. It should be noted that both estimation methods can provide rather accurate weight estimation using only the mid-span ($L/2$) bending moment as the input even though the number of vehicle axle is 2.

This obtained result implies that the application of the two methods can be extended to the case where multiple vehicles are simultaneously presented on the bridge using only limited number of measuring sections of bridge bending moments. It should be noted that the estimation errors of the rear axle and the gross weights of the vehicle from both Method I and Method II can be kept smaller than 5% for considered range of noise levels using only one measuring section of the bridge. It is also observed that increasing the number of measuring sections beyond 3 does not significantly improve the accuracy of the two weight estimation methods. Comparing the errors from the two estimation methods, it is found that Method II yields slightly smaller errors than Method I for all considered number of measuring sections and noise levels.

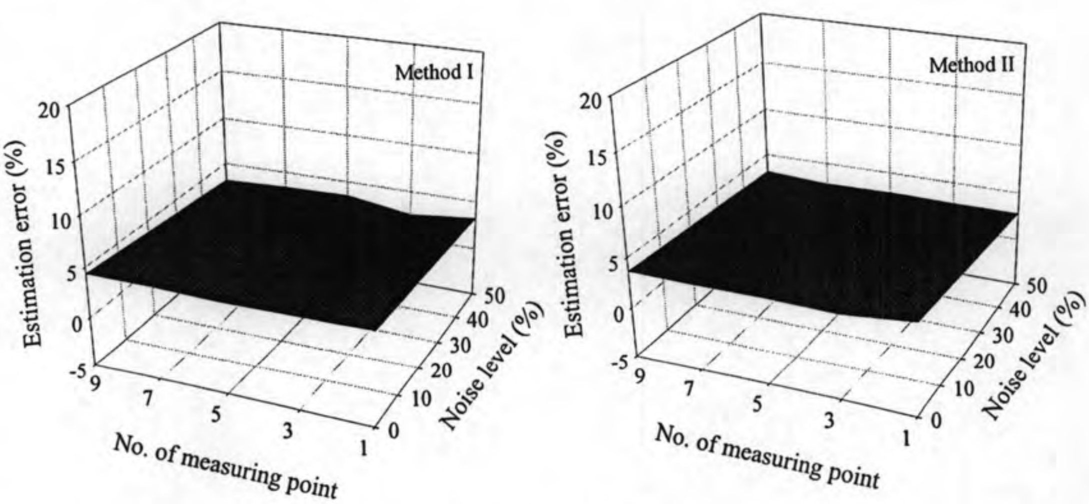
From the identified dynamic axle loads resulting from Method II, it is observed from the figure that the load identification error is significantly affected when noise level are more than 10%. This is because the noise effect disturbs the bending moment responses for identifying the dynamic axle loads. In general, the noise level in laboratory test and field test are usually lesser than 10% of the highest magnitude of measured responses. Therefore, in Figure 4.6, it is shown that three measuring sections provide sufficient accuracy for the real application (with the noise levels < 10%).



(a) Front axle weight

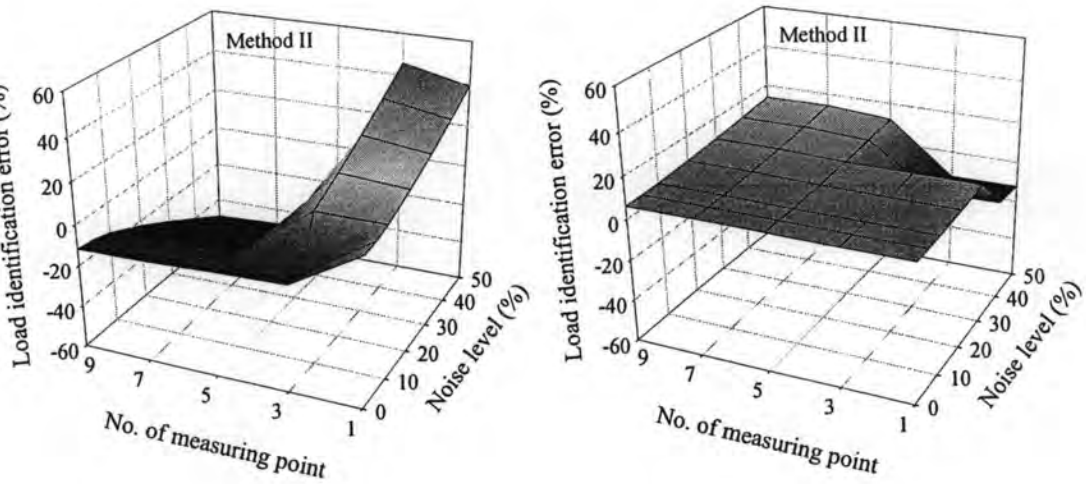


(b) Rear axle weight



(c) Gross weight

Figure 4.5 Estimation errors of the axle weights under various number of measuring points and noise levels for (a) front axle weight (b) rear axle weight (c) gross weight



(a) Front axle load (b) Rear axle load

Figure 4.6 Identification errors of the axle loads of Method II under various number of measuring points and noise levels for (a) front axle load (b) rear axle load

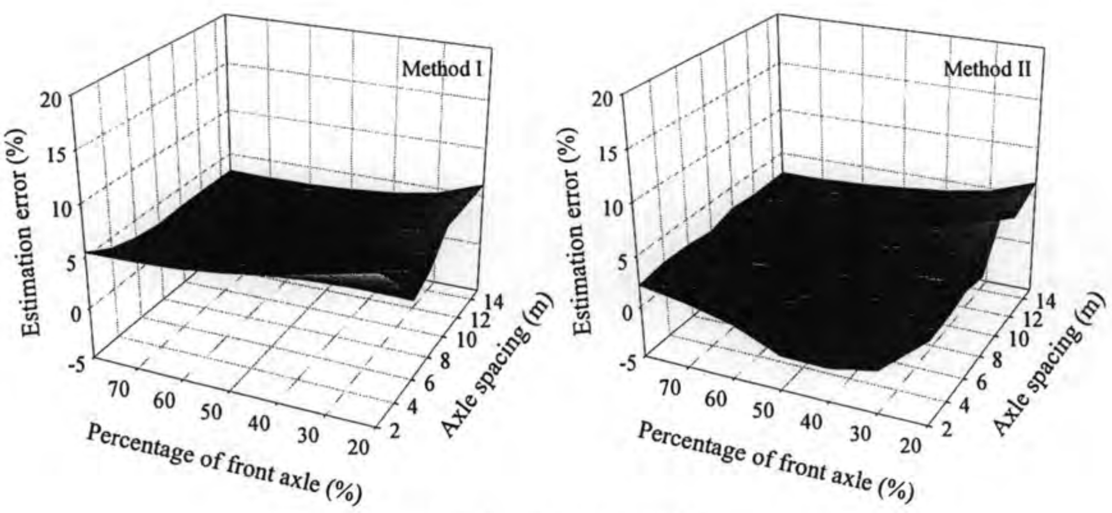
Table 4.4 Measuring point arrangement

Number of Measuring point	Location
1	1/2*L*
3	1/4*L*, 1/2*L*, 3/4*L*
5	1/8*L*, 1/4*L*, 1/2*L*, 3/4*L*, 7/8*L*
7	1/8*L*, 1/4*L*, 3/8*L*, 1/2*L*, 5/8*L*, 3/4*L*, 7/8*L*
9	1/8*L*, 1/4*L*, 3/8*L*, 7/16*L*, 1/2*L*, 9/16*L*, 5/8*L*, 3/4*L*, 7/8*L*

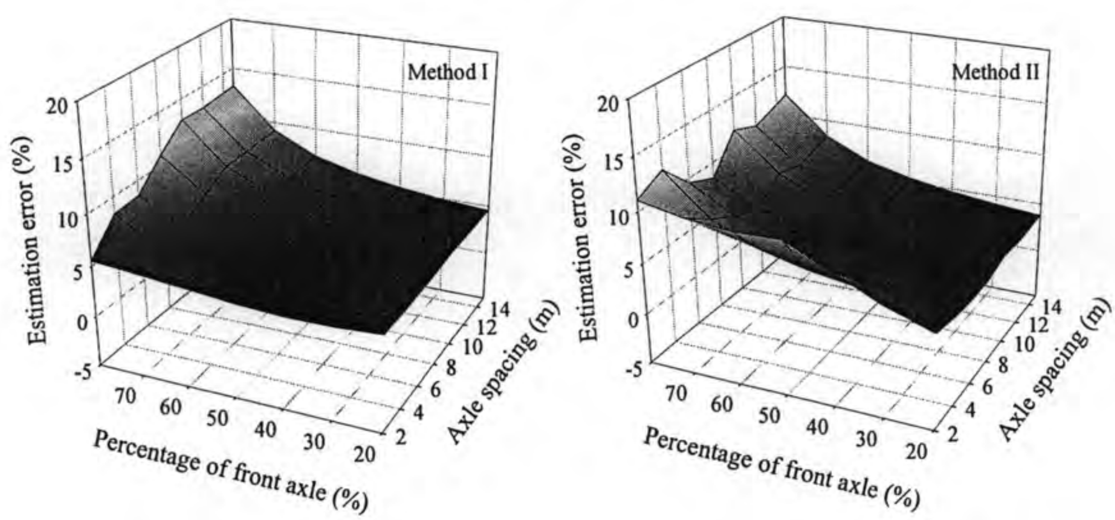
4.3.4 Effects of Axle Spacing and Axle Weight Distribution

The effects of axle spacing and axle weight distribution of the vehicle on the accuracy of the weight estimation methods are investigated. The axle spacing of the vehicle from 2 to 15 m and the axle weight distribution of the vehicle defined by the ratio of the front axle weight to the gross weight are considered. The vehicle having different axle spacing and axle weight distribution moving on the bridge at a constant speed of 15 m/s is simulated. The bridge surface is assumed to have the roughness of level 3. Based on the obtained bridge moments at three sections, i.e. $L/3$, $L/2$ and $2L/3$, the axle weights of the vehicle are estimated using Method I and Method II. Figures 4.7(a) to 4.7(c) show the estimation errors of the front axle, rear axle, and gross weights of the vehicle from the two methods under various axle spacings and axle weight distributions. The obtained results in Figure 4.7(c) clearly indicate that the estimation error of gross weight is slightly affected by both axle spacings and axle weight distributions. However, their effects on the estimation errors of the front and rear axle weights as in Figures 4.7(a) and 4.7(b) are found to be significant. These errors increase as the axle weights are reduced. This is mainly because the estimation error is computed in term of percentage error with respect to the corresponding actual weight. Therefore, with the same amount of weight error, an axle with lighter weight would give a higher percentage of error. In particular, the estimation errors of the gross weights using Method II are varied from 3.1 to 4.6 % and using Method I are varied from 3.9 to 5.5 %. Comparing the errors from the two estimation methods, it is also found that Method II yield slightly smaller errors than Method I especially for the lower axle weight distribution.

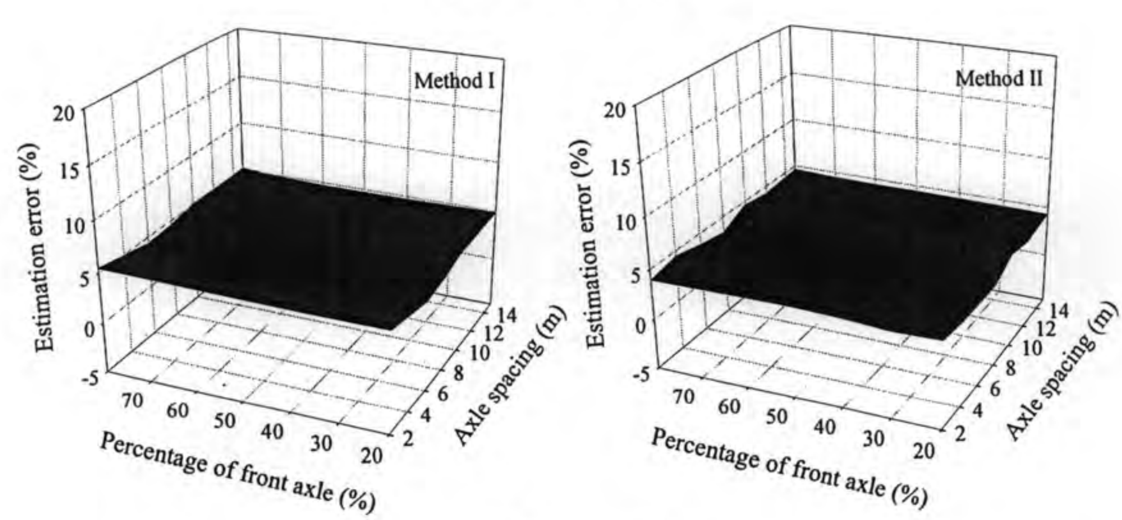
From the identified dynamic axle loads resulting from Method II, the obtained results indicate that the axle weight distribution affects the identification accuracy as well as the axle spacing. An axle with heavier weight can be identified with more accuracy than an axle with lighter weight. This is because the identification error is calculated in the term of percentage value. From the identification results with various axle spacings, it is observed that axle load identification for a vehicle with closely spaced axles results in a larger load identification error than identification for a vehicle with wider axle spacing. This is because the bridge response in the case of closely spaced axles is nearly indistinguishable from the response induced by a vehicle with a tandem axle configuration. Therefore, the closely spaced axle loads become more difficult to be accurately identified.



(a) Front axle weight

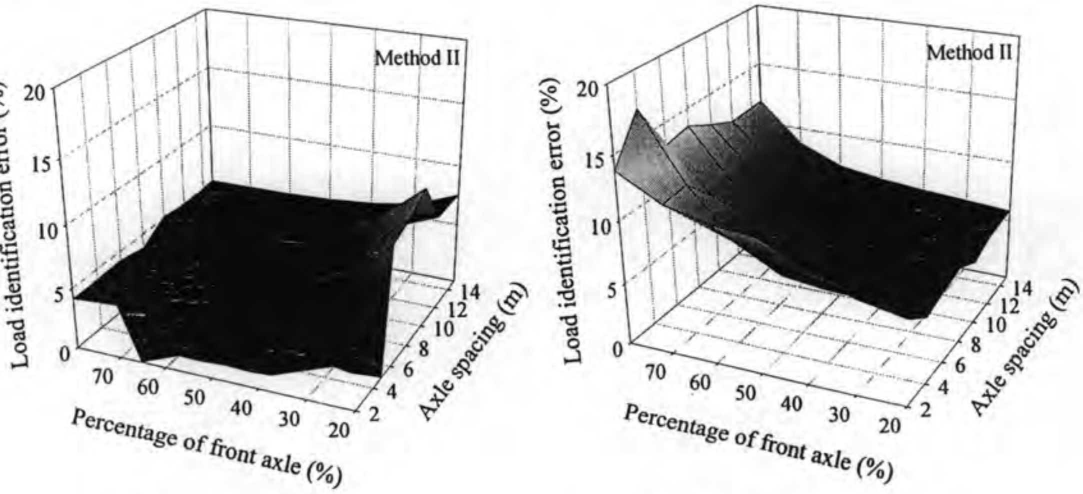


(b) Rear axle weight



(c) Gross weight

Figure 4.7 Estimation errors of the axle weights under various axle spacings and axle weight distributions for (a) front axle weight (b) rear axle weight and (c) gross weight



(a) Front axle load (b) Rear axle load

Figure 4.8 Identification errors of the axle loads of Method II under various axle spacings and axle weight distributions for (a) front axle weight (b) rear axle weight

4.3.5 Robustness of Methods from the Error of Measurement

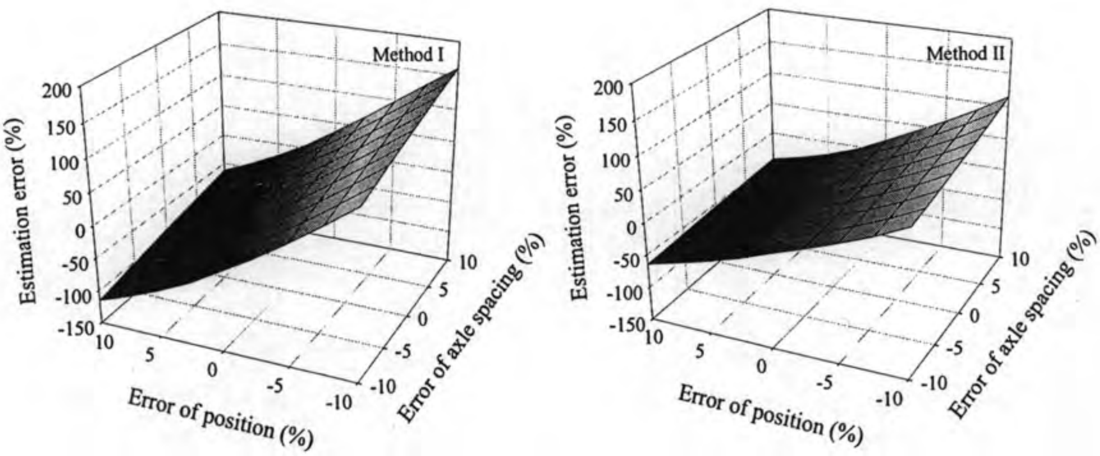
The robustness of the axle load identification methods from the error of measurement is investigated. In the real application, the error from measurement such as: the axle spacing of vehicle and the position of vehicle on the bridge can be occurred. The errors from measurement of the vehicle axle spacing and the position of vehicle on the bridge measurement are varied with the range -10% to 10%. The vehicle moving at a constant speed of 15 m/s on the bridge having the roughness of level 3 is simulated. Based on the obtained bridge moments at three sections, i.e. $L/3$, $L/2$ and $2L/3$, the axle weights of the vehicle are estimated using Method I and Method II.

The obtained results in Figures 4.9(a) to 4.9(c) show that the effect from the error of position measurement distorts the percentage error of axle weight higher than the effect from error of axle spacing measurement. This is because the position of the vehicle significantly affects the computation method. The strain signal is conducted when the vehicle is moving on the bridge. The algorithm of a program computes the axle load which is optimized with strain signal. Consequently, the error of measurement position of vehicle on the bridge produces the strain signal before or after the vehicle is on the bridge in the real situation. Figures 4.9(a) to 4.9(c) indicate that the errors from Method II are lower than Method I in all cases. The percentage errors are observed in gross weights from Method II of between -10% and 10%, and from Method I of between -20% and 15%.

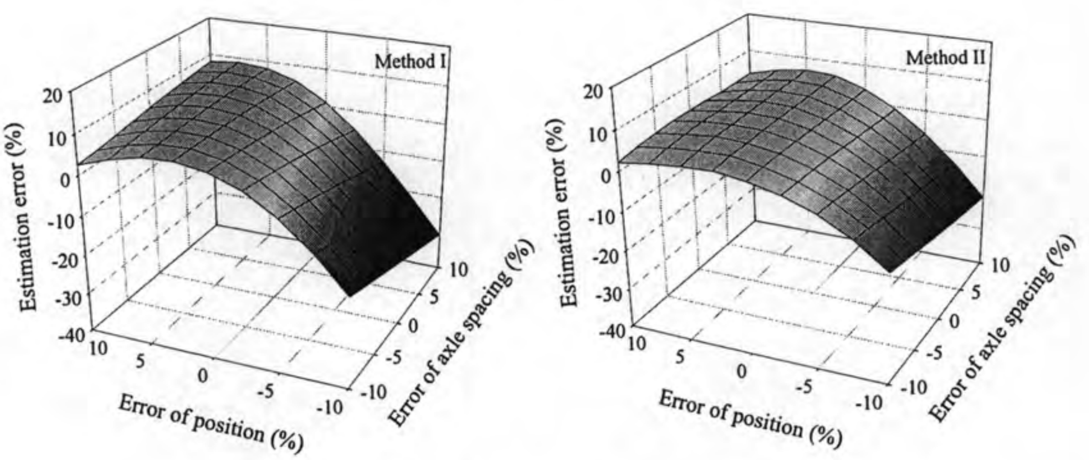
Figure 4.10 shows the result in relative percentage error of the vehicle axle loads. It is found that the relative percentage of the axle load identification error is significantly affected by the error of position measurement higher than the effect from the error of axle spacing measurement. This is because of the same reason which is explained in the previous part.

4.3.6 Random Simulation

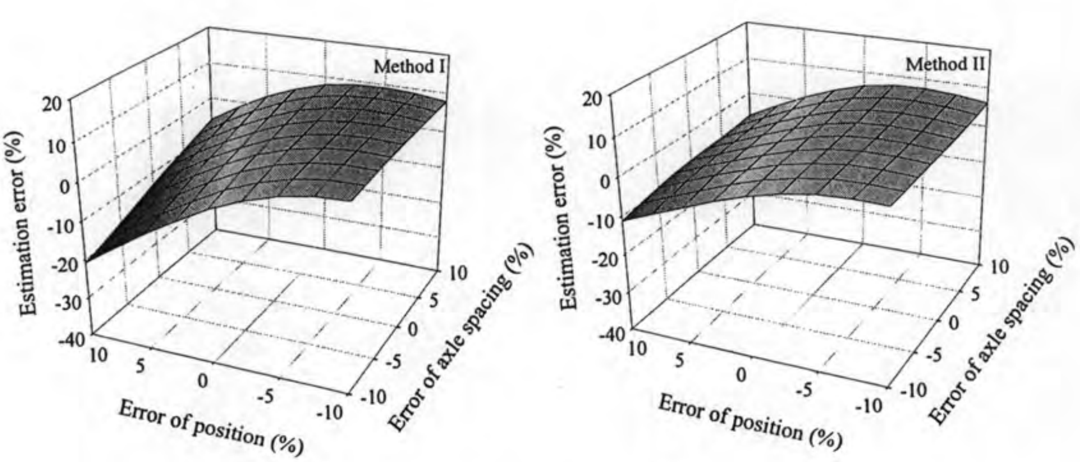
It is evidenced from previous numerical examples that the effectiveness of the axle load identification methods depends on many relevant parameters such as vehicle speed, vehicle configuration, vehicle weight and bridge surface roughness. Therefore, the following study investigates the effectiveness of the two identification methods through numerical simulations of 1,000 cases of vehicle-bridge interaction system. Seven parameters of the vehicle-bridge system, consisting of vehicle speed, vehicle gross weight, vehicle weight distribution, axle spacing, suspension stiffness, roughness profile and roughness level, are considered. The values of these parameters are assumed to be uniform random within their ranges given in Table 4.5 Other parameters of the vehicle-bridge system are set to values as previously listed in Table 4.1 Based on the bridge bending moments at three sections, i.e. $L/3$, $L/2$ and $2L/3$, under a passage of the vehicle, the axle weights of the vehicle are estimated using Method I and Method II. In all cases, the bridge is discretized into 8 beam elements and the sampling frequency of the moments is set to 500 Hz. It is noted that, for each random case, the error of ± 10% of axle spacing resulting from the position sensors is also taken into account.



(a) Front axle weight

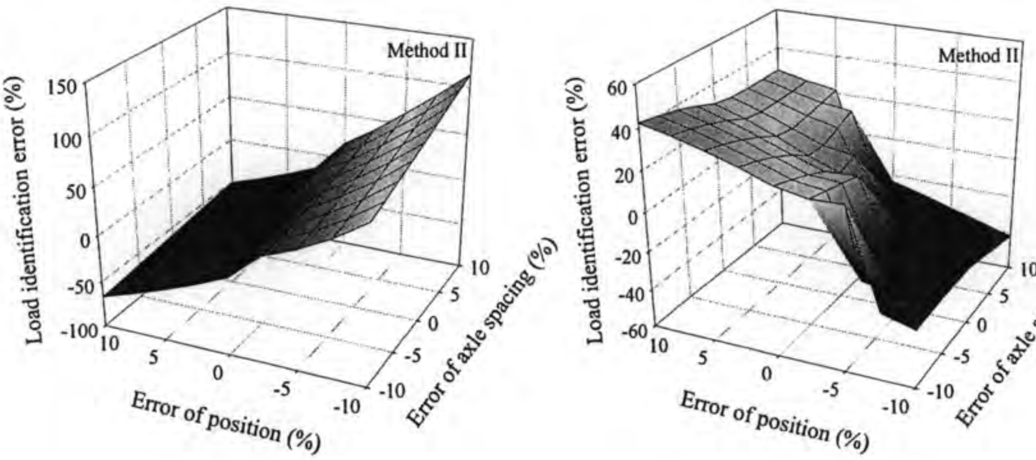


(b) Rear axle weight



(c) Gross axle weight

Figure 4.9 Estimation errors of the axle weights under different errors of position and errors of axle spacing for (a) front axle weight (b) rear axle weight (c) gross weight



(a) Front axle load (b) Rear axle load

Figure 4.10 Identification errors of the axle loads of Method II under different errors of position and errors of axle spacing for (a) front axle load (b) rear axle load

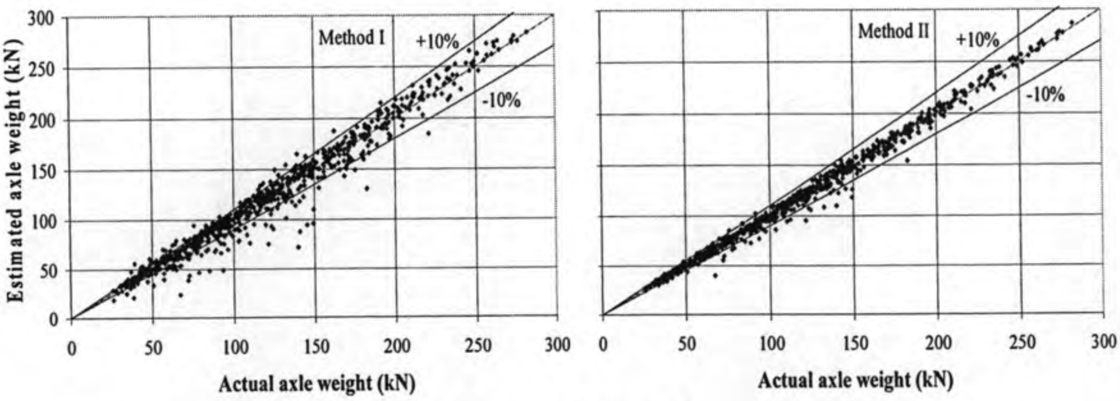
Table 4.5 The parameters of bridge and vehicle system for random simulation

Bridge parameters	
Roughness profile	5 profiles
Roughness level	4 levels
Vehicle parameters	
Gross weight	10 to 50 Tons
Weight distribution	20 to 80% (front axle weight per total weight)
Vehicle stiffness parameters	-30 to 30% (%of stiffness as listed in Table 4.1)
Velocity of vehicle	1 to 40 m/s
Axle spacing	2 to 10 m
Axle spacing measurement error	-10 to 10% (% of axle spacing)

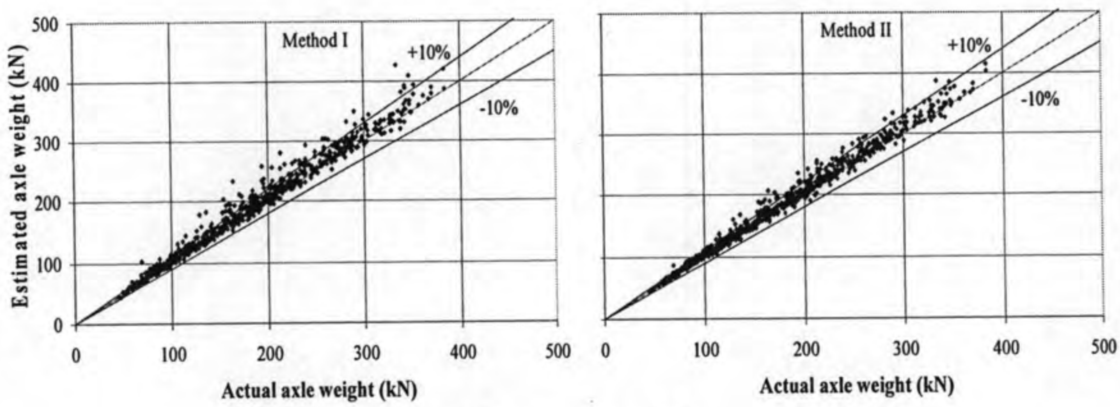
The relationships between the actual and the estimated weights of the front axle, rear axle and total weight of the vehicle from the two methods are shown in Figures 4.11(a) to 4.11(c), respectively. The statistical values of the obtained results are listed in Table 4.6. It is obvious from the figures, although there are certain cases that the estimation errors are rather high, that the two methods provide quite accurate weight estimations of the vehicle, i.e. errors < ±10%, in almost of the 1,000 cases. Since both methods tend to under-estimate the weight of the front axle but over-estimate the weight of the rear axle, consequently, the estimation errors of gross weight becomes relatively smaller. For examples, the largest estimation errors of the front and rear axles from Method I can be, respectively, as high as -64.72% and +47.90%. However, the largest error of the corresponding gross weight from the same method is reduced to only +15.10%. The similar characteristic is also found when using the Method II. Comparing the two methods, it is clearly seen that Method II is superior in all cases. More precisely, the maximum, minimum, average, and standard deviation values of the estimation error from Method I are all significantly larger than those from Method II as shown in Table 4.6.

Table 4.6 Error of vehicle weight from estimation results

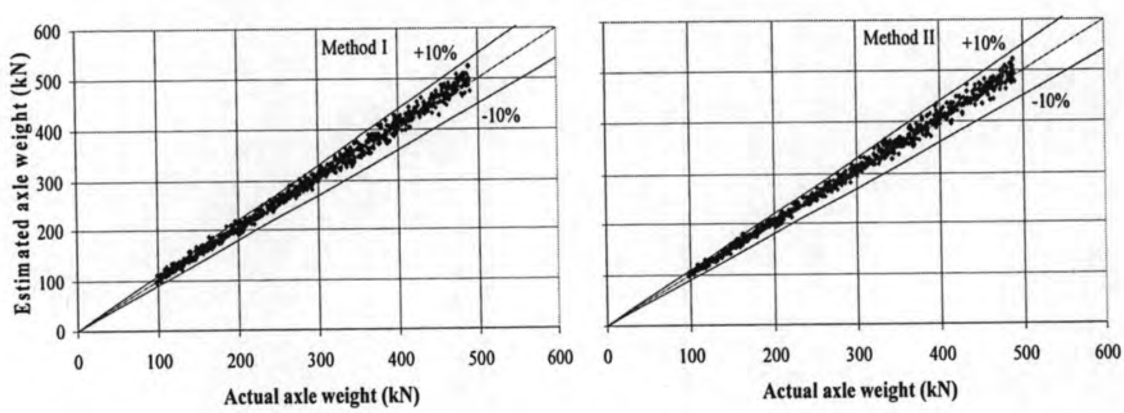
Method	Weight	Min (%)	Max (%)	Mean (%)	SD
I	Front Axle	-64.72	41.27	-0.53	9.72
	Rear Axle	-7.74	47.90	4.21	6.24
	Gross weight	-5.92	15.10	2.57	3.09
II	Front Axle	-41.01	11.90	-0.62	4.71
	Rear Axle	-7.52	25.62	3.58	4.54
	Gross weight	-4.74	11.14	2.00	2.66



(a) Front axle weight



(b) Rear axle weight



(c) Gross weight

Figure 4.11 The relationships between the actual and the estimated weights of the front axle, rear axle and gross weight of the vehicle from the two methods

It is interesting to investigate the influence level from each considered parameter. To do so, the correlation concept which can indicate the level of linear dependency between the function and its parameters is adopted. Thus the correlation coefficients of the weight estimation errors from the two methods and the vehicle-bridge system parameters are computed and are shown in Table 4.7. It should be observed that the correlation coefficients of all parameters from Method I and Method II are very close. Among them, the correlation coefficients of the axle spacing, the vehicle speed and the measurement error of axle spacing seem to be rather high. In particular, the extreme values of about -0.40, +0.60 and +0.65 of, respectively, the axle spacing, the vehicle speed, and the measurement error of axle spacing are obtained. The results imply strong influences of these three parameters on the weight estimation errors from the two methods.

Table 4.7 Correlation coefficients between the estimated vehicle axle weight and the various parameters

Method	Axle weight	Rough. level	Gross weight	Weight distribution	Vehicle parameters	speed	Axle spacing	Meas. error
I	Front	0.07	-0.09	0.22	0.08	-0.16	0.26	0.61
	Rear	0.09	-0.02	-0.05	-0.05	0.56	-0.36	-0.19
	Gross	0.18	-0.12	0.03	0.06	0.52	-0.14	0.46
II	Front	0.11	-0.08	0.23	-0.06	-0.19	0.24	0.63
	Rear	0.10	0.02	0.01	0.04	0.58	-0.37	0.19
	Gross	0.15	-0.03	-0.01	-0.06	0.51	-0.19	0.60

Since the measurement error of axle spacing can be practically kept within ±5% using the existing present measurement technology, the simulation cases where the measurement errors of axle spacing exceed ±5% are omitted and the effectiveness of the two methods in term of 95% probability of conformity are calculated from about 500 remaining cases and are shown in Table 4.8. The table indicates that Method II exhibits lower estimation errors of front axle, rear axle and gross weights of vehicle than Method I. Using Method II, the reductions of estimation errors of 6.6%, 5.1% and 2.7% over those using Method I are apparent for the front axle, rear axle and gross weights. It should be noted that, comparing with the tolerances limited by the ASTM standards, the obtained results from Method I and Method II are capable of achieving the accuracy level of the WIM system of type-I and type-III, respectively.

Table 4.8 The vehicle axle weight estimation error from 500 cases random simulations at 95% probability

Method	Front axle weight (%)	Rear axle weight (%)	Gross weight (%)
I	13.5	16.6	8.2
II	6.9	11.5	5.5
ASTM Type I	20.0	20.0	10.0
ASTM Type III	15.0	15.0	6.0

4.4 Summary

The effectiveness of the vehicle axle load identification from the bridge bending moment is studied. The measured bending moments of the simply-supported bridge at selected sections under a passage of the vehicle are numerically simulated and are used as the input for the vehicle axle load identifications. Two axle load identification methods assuming constant magnitudes (Method I) and time-varying magnitudes (Method II) of the vehicle axle loads are investigated. Their identification accuracy are evaluated and compared under various parameters of the vehicle-bridge system.

It is found that, to guarantee the highest accuracy of the weight estimations, the bridge should be discretized with certain refinement and its bending moment signals should also be sampled with rather high frequency. Based on the simulation results, the minimum number of bridge discretization of 4 and the minimum sampling frequency of 50 Hz are obtained. It should be noted that the three measuring sections are sufficient for the 2-axle loads identification. The efficient number of finite beam elements employed in structural modeling is 8 elements for a bridge with 10 m span length. The sampling rate recommended to be used in data acquisition system is at least the five modes fundamental frequency of the bridge. It is also found that, among seven considered parameters, the vehicle speed, the surface roughness and the error of measurement seem to have stronger effect on the accuracy of the two identification methods than the others. However, the estimation errors of the gross weight of the vehicle can be controlled to be within ±10% if the surface roughness is kept below level 4, regardless of the vehicle speed.

In general, both methods can provide quite accurate weight estimation. Based on the 1,000 cases of random simulation, the errors of the gross weight of the vehicle from the two estimation methods are found to be within ±10%. It is observed that they tend to underestimate the front axle weight but overestimate the rear axle weight. As the result, the smaller errors of the gross weight estimation than those of the corresponding front and rear axle weights can be expected.

Since the measurement error of axle spacing can be practically kept within ±5% using the existing present measurement technology, the simulation cases where the measurement errors of axle spacing exceed ±5% are omitted and the effectiveness of the two methods in term of 95% probability of conformity are calculated from about 500 remaining cases. The results indicate the achievability of the accuracy level of the WIM system of ASTM standard type-I for Method I and ASTM standard type-III for Method II, respectively.

Although Method II exhibits approximately slower speed of computation than Method I. The obtained results indicate that it can provide better weight estimation for almost of the considered cases. Moreover, Method II also provides identified dynamic axle loads. Compared with the tolerances limited by the ASTM standards, it is found that Method II is capable of achieving the accuracy level of the WIM system of type-III.