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Automatic measurement of payload for heavy vehicles using strain gages

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Abstract

Accidents caused by heavy vehicles have been increasing in recent years. This is mainly due to the fact that vehicle overloading results in steering difficulty and long braking distance. Therefore, this work aims to develop an automatic payload measurement for heavy vehicles, so that drivers and police officers can monitor vehicle payload while on board the measured vehicle. For the ease of installation, high accuracy, and low cost, this work proposes to paste strain gages onto each leaf spring in vehicle suspensions. Based on measured output voltages of bridge circuits in each suspension, the vehicle payload is calculated. Moreover, for promoting the accuracy of calculated payload, this work develops neural network models to account for nonlinearity in measurement. Finally, this work verifies model accuracy based on experimental data.
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1. Introduction

Overloading of heavy vehicles results in road damage, short vehicle life, and vehicle maneuver difficulty. Heavy vehicle accidents may also cause serious casualties. Therefore, in addition to careful driving, overload avoidance of heavy vehicles is also an important issue in preventing traffic accidents. A truck scale is a common device for measuring the weight of a heavy vehicle. However, truck scales are usually installed at fixed locations, which are not convenient for police to check vehicle payload on the road.

Many devices for vehicle payload measurement have been developed. Nishitani [1] installed a linking device between the suspension and the body of a heavy vehicle to measure the vehicle's payload which uses an electro-magnetic sensor in the device that generates associated output voltage according to the payload. The vehicle weight is hence derived based on the voltage. In no. 5684254 of the United States Patent, Nakazaki et al. [2] presented a payload measurement method by measuring suspension strain caused by payloads. Generally, leaf springs are used in the suspension system of a heavy vehicle.

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Different solutions for measuring different types of leaf springs are described in patents. However, applying different types of measuring devices to different types of vehicles leads to inconvenience in use, which is the drawback of this approach. Accordingly, a method that can be used for various types of vehicles is presented in this study. Strain gages are pasted on each suspension leaf spring in a vehicle and hence the payload is calculated based on voltage signals of strain gages. Experiments for the proposed method have been conducted on a real vehicle. The payload of the vehicle is obtained by summing load readings in all suspensions; but resultant errors vary in a wide range. To reduce the error, neural network models that can account for nonlinearity in measurement are developed in this study.

With capabilities of filtering, adaptive learning, etc., neural network can be used to deal with linear and nonlinear problems. Hence, they have been widely used in many aspects such as simulation for the PH-value variation of a chemical combining vessel [3], the solution of a chaos problem [4], the prediction of a river level [5], and even dealing with a financial problem [6]. This study verifies the accuracy of the proposed neural network models based on experimental data.

Section 2 presents the experiment setup and the results for a truck trailer. Section 3 presents the neural network models used to reduce calculated payload error. Section 4 concludes this work.

2. Experiment for truck trailer

2.1. Electric circuits

To install the proposed apparatus on trailer suspensions, this work in advance prepares a Wheatstone bridge, zero-returning circuit, voltage regulator, and instrumentation amplifier:

2.1.1. Zero-returning circuit

The output of a bridge circuit comes from the resistance variation of the sensor on the bridge; resistors used for the arms of the bridge should be precise and stable. Metal-film resistors are used for the bridge in this work. Since the resistance error of the strain gage ($120.4 \pm 0.4 \, \Omega$) is greater than the resistance error of the bridge resistor ($120 \pm 0.012 \, \Omega$), the bridge is not balanced at no-load situation. Therefore, a zero-returning circuit, as shown in Fig. 1, is needed. This circuit returns the output
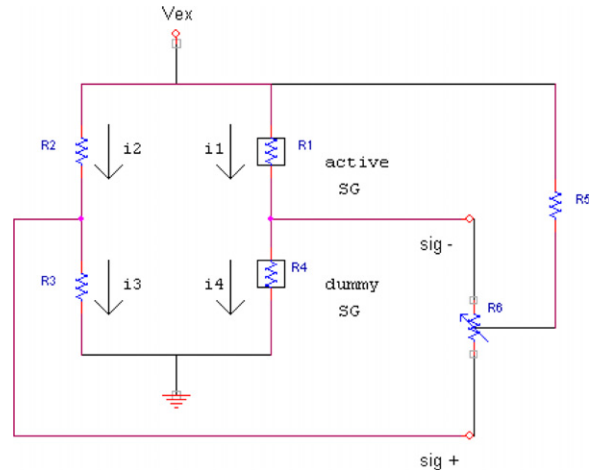

Fig. 1. Zero-returning circuit.

of the bridge to zero by adjusting the R6 resistor. It is found during the experiment that the value of R6 affects both the sensitivity and the stability of the circuit at the same time. The circuit has higher stability but lower sensitivity when R6 is small. In contrast, large R6 promotes the sensitivity but degrades the stability. How to compromise and end up with an optimal value is an issue of this experiment. In this work, R5 is set to be $10 \, \Omega$ and R6 is designed to be a 25-turn variable resistor of $10 \, \Omega$ with a $1000 \, \Omega$ resistor connected to each side, i.e. R6 varies between $2000 \, \Omega$ and $2010 \, \Omega$ by turning the variable resistor. This configuration results in the ease of zero-returning and maintaining the sensitivity.

2.1.2. Voltage regulator

Since the input voltage of a bridge directly affects the output, a voltage regulator for supplying a stable input voltage is required to generate accurate bridge output. An IC of model LM317 made by National Semiconductor is adopted to complete the regulator circuit depicted in Fig. 2 and supply 2.5 V in this experiment.

2.1.3. Instrumentation amplifier

An instrumentation amplifier IC of model INA131 made by Burr-Brown chip is employed to do signal conditioning for the output signal of the bridge. The IC circuit and its frequency response are shown in Fig. 3. The IC gain is 100.057 when there is no external resistor added. However, the gain can be adjusted by connecting an extra resistor
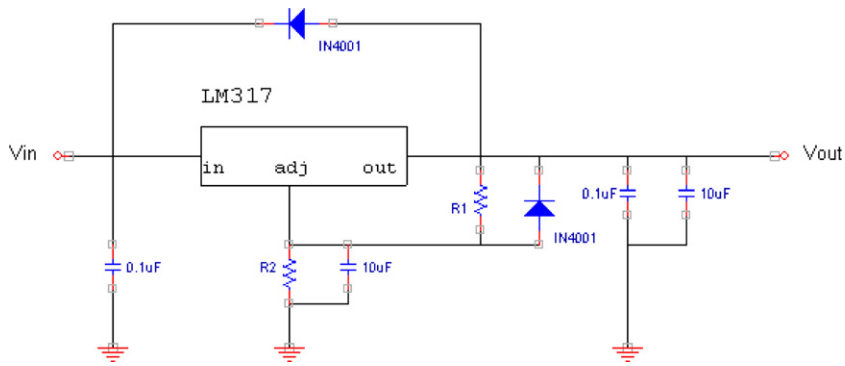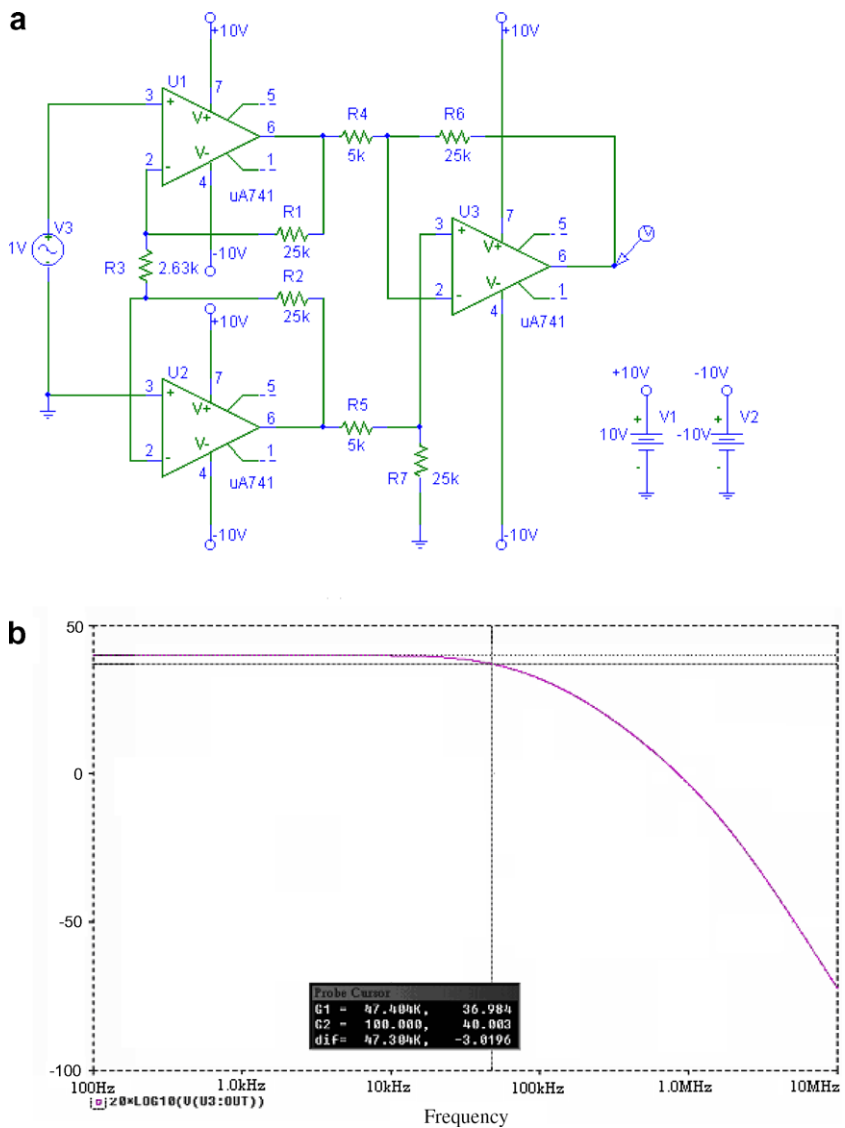
Fig. 2. Regulator for supplying 2.5 V.

Fig. 3. Frequency response of instrumentation amplifier IC. (a) Circuit for simulation; (b) response.

R_G to be parallel with R_3. The adjusted gain value is formulated as

$$
\begin{aligned}
G &= \left(1 + \frac{2R_1}{(R_3//R_G)}\right) \times \left(\frac{R_6}{R_4}\right) \\
&= \left[1 + \frac{2 \times 25k}{\left(\frac{1}{\frac{1}{2.63k} + \frac{1}{R_G}}\right)}\right] \times \left(\frac{25k}{5k}\right) \\
&= 100.057 + \frac{250k}{R_G}.
\end{aligned} \tag{1}
$$

2.2. Measurement for truck trailer

The vehicle measured in experiments is a truck trailer with empty mass 10,040 kg that has been measured by a truck scale as shown in Fig. 4. The mass of the left, right, front, and rear portion of the truck is measured as 4870 kg, 4770 kg, 3840 kg, and 6240 kg, respectively. Accordingly, the center of gravity of the truck is not on the centerline. Dimensions of the truck are shown in Fig. 5. The truck's suspensions are denoted as Left-Front (LF), Left-Rear (LR), Right-Front (RF), and Right-Rear (RR), respectively. A set of strain gages are pasted on each of the four suspensions after the leaf spring surface is cleaned. Fig. 6 shows the strain gages pasted on the surface of leaf springs in the RR

suspension. In conducting this experiment, two kinds of objects are respectively used as payloads: truck tires and a car. The results are described below.

2.2.1. Results of using truck tires as payload

The mass of each tire used in the experiment is 67 kg. The gains of the four amplifiers for the four bridges are all set at 1141 that is calculated according to Eq. (1) by prescribing $R_G = 240 \, \Omega$. Fig. 7 shows resulting output voltage versus tire quantity in four experiments that are conducted by loading 0–21 tires on the left, right, front, and rear side of the trailer, respectively. As depicted in Fig. 7(a), i.e. when tire loads are applied at the left side of the truck as shown in Fig. 8, both LF and LR curves go upward whereas both RF and RR curves go downward with increasing load. This implies that leaf springs on the left-hand side are in tension whereas those on the opposed side are in compression. This results from inclination of the truck trailer body when loads are placed on the left side. Similar results can be observed in the other three experiments, i.e. Fig. 7(b)–(d).

In contrast to vehicle leaning in previous four experiments, the fifth experiment is performed by placing tires at four corners inside the trailer. Fig. 9 shows the results, where the same number of tires are placed at each corner in the trailer at

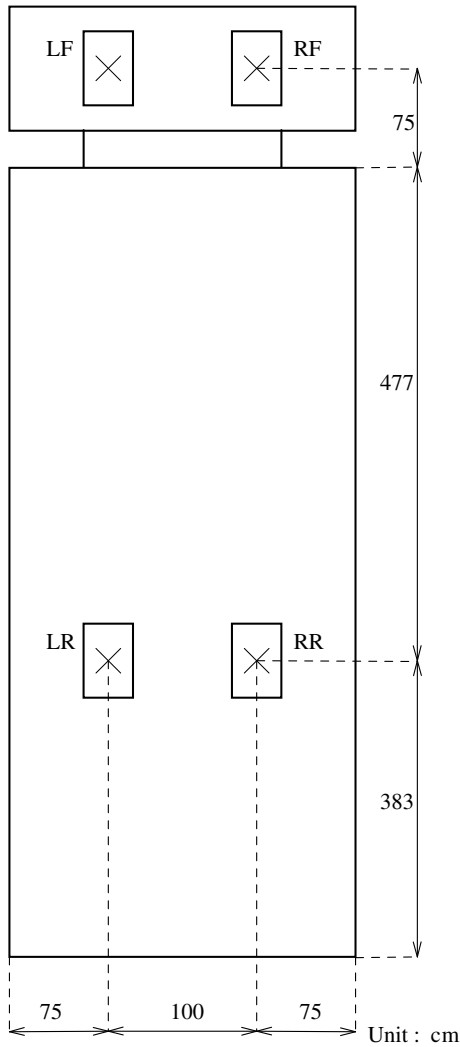
Fig. 4. Photo of truck weighed on truck scale.

Fig. 5. Truck dimensions.

Fig. 6. Pasted strain gages on rear suspension. (a) Overall view; (b) close-up view.

the same time. Accordingly, 24 tires in total are placed inside the trailer when fully loaded.

For converting the measured strain gauges voltage to the payload, the load applied to each suspension should be known beforehand. In Fig. 10, the cross mark denotes the center of gravity of the payload. The value is represented by W. From the side view of the truck in Fig. 10, the following equations can be derived in accordance with force balance and torque balance:

$$(P_{LF} + P_{RF}) + (P_{LR} + P_{RR}) = W, \tag{2}$$

$$(P_{LF} + P_{RF}) \times (L_1 + L_2) = W \times L_2, \tag{3}$$

$$(P_{LR} + P_{RR}) \times (L_1 + L_2) = W \times L_1. \tag{4}$$

where P_{LF}, P_{RF}, P_{LR}, and P_{RR} represent loads applied to suspensions LF, RF, LR, and RR, respec-
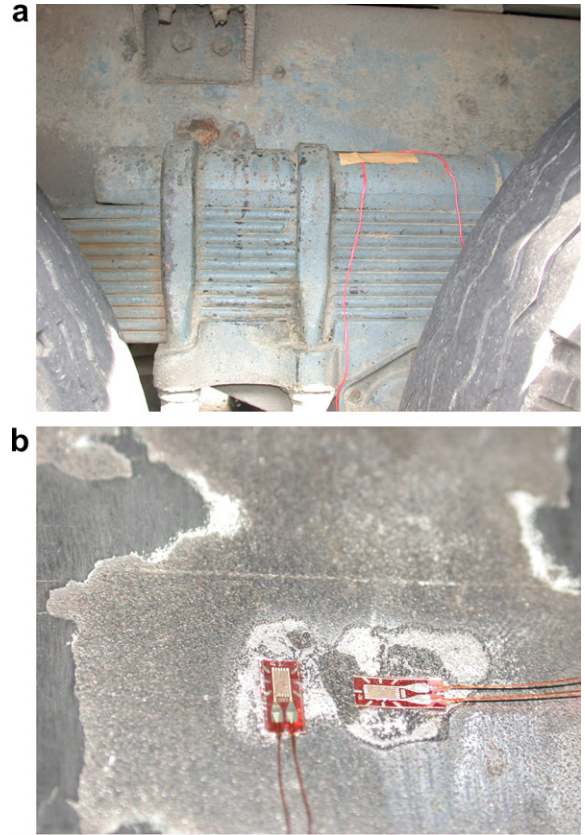
tively. Between front suspensions LF and RF, the following equation can be derived:

$$P_{LF} \times L_3 = P_{RF} \times L_4. \tag{5}$$

In a similar manner, between rear suspensions LR and RR, the equation can be formulated as

$$P_{RR} \times L_4 = P_{LR} \times L_3. \tag{6}$$

Solving Eqs. (3)–(6) yields

$$P_{LF} = W \times \frac{L_2}{L_1 + L_2} \times \frac{L_4}{L_3 + L_4}, \tag{7}$$

$$P_{RF} = W \times \frac{L_2}{L_1 + L_2} \times \frac{L_3}{L_3 + L_4}, \tag{8}$$

$$P_{LR} = W \times \frac{L_1}{L_1 + L_2} \times \frac{L_4}{L_3 + L_4}, \tag{9}$$

and

$$P_{RR} = W \times \frac{L_1}{L_1 + L_2} \times \frac{L_3}{L_3 + L_4}. \tag{10}$$
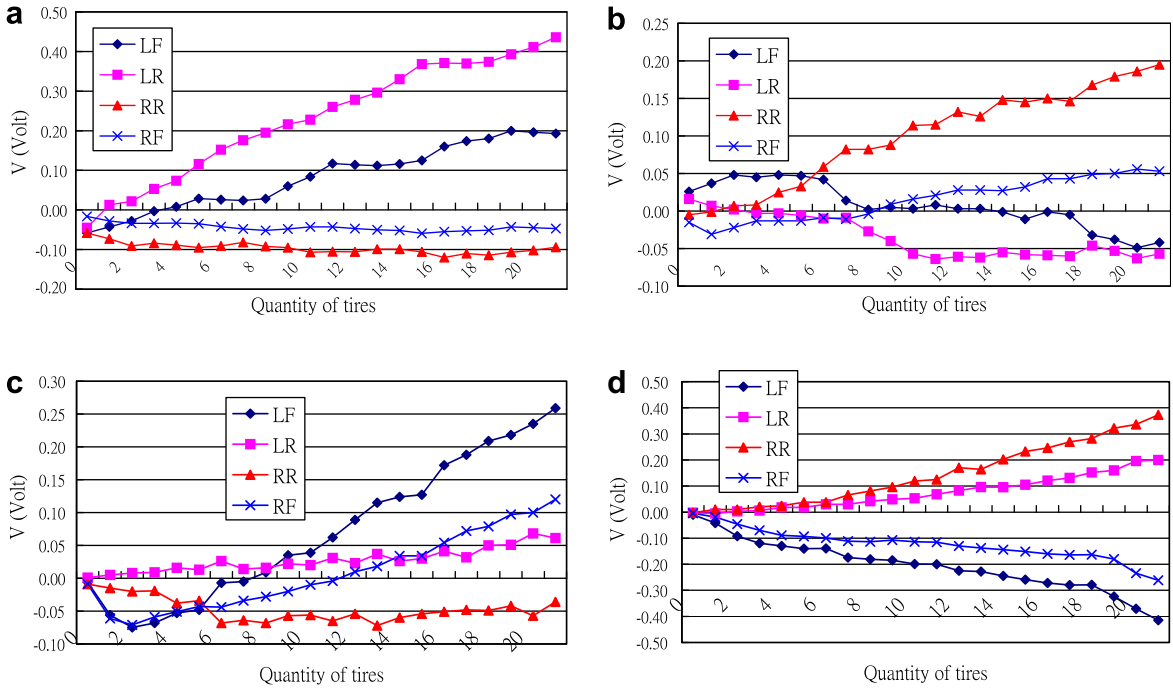
Fig. 7. Experimental results of using truck tires as payload. (a) Left side; (b) right side; (c) front side; (d) rear side.

To obtain larger output voltages, gains of the amplifiers for front suspensions and rear suspensions are reset as 6350 and 2183 by prescribing $R_G = 40\,\Omega$ and $R_G = 120\,\Omega$, respectively. Using the new gains to do the five experiments all over again, the results of the right side experiment as shown in Fig. 11 are chosen as the representative due to its best linearity. Calculating loads for each suspension according to Eqs. (7)–(10), the results of 21 tires, in contrast to 24 tires in the four-corner experiment, are shown in Table 1. According to Fig. 11 and Table 1, equations for converting measured voltages (V) to loads (kg) of each suspension are derived as follows:

$$P_{LF}(kg) = 143.269 \times V_{LF}(V), \qquad (11)$$

$$P_{LR}(kg) = 2178.224 \times V_{LR}(V), \qquad (12)$$

$$P_{RR}(kg) = 3857.822 \times V_{RR}(V), \qquad (13)$$

$$P_{RF}(kg) = 157.012 \times V_{RF}(V). \qquad (14)$$

2.2.2. Results of using a car as payload

The purpose of using a car as payload is to avoid spending time manually moving tires one by one. Instead, it is easier to move a car into the trailer so as to acquire more experimental data. The car mass is 1210 kg. The car was parked on the front

side and rear side of the trailer, and five points on each side were measured. The same experiment was conducted again on the next day. In Fig. 12, the representations of symbols 1F, 1R, 2F, and 2R on the transverse are: the first day data measured when the car was parked on the front side, the first day data measured when the car was parked on the rear side, the second day data measured when parked on the front side, and the second day data measured when parked on the rear side, respectively. Converting the measured voltages in Fig. 12 of each suspension to loads in accordance with Eqs. (11)–(14), adding the resultant four loads, and the payload is thus derived. The error percentages of the derived payloads are shown in Table 2. The largest value is 74%, which is unacceptable. Because the leaf spring is bent, it should have different characteristics between compression and tension. Therefore, a neural network is employed to reduce errors.

There is one thing worth mentioning. The weather was windy during those days on which the experiments were performed. Strong wind shook the truck trailer body, which led to flickering of displayed data, making data reading difficult. The experiment hence had to be postponed until the wind subsided for better data readability.
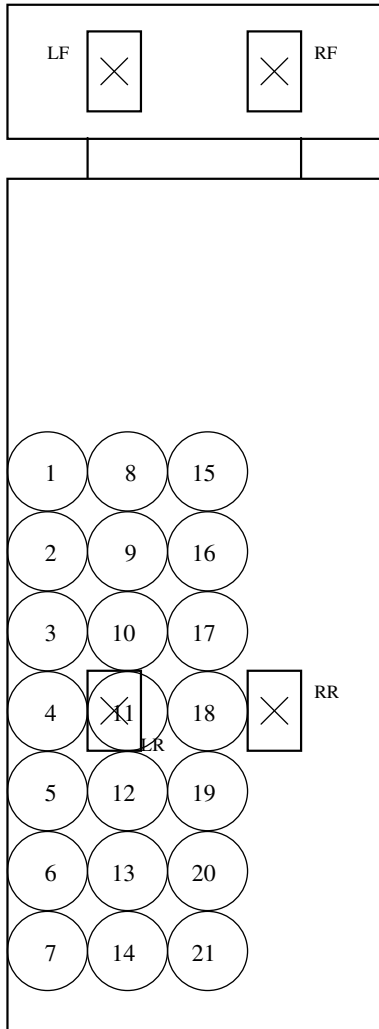
Fig. 8. Schematic diagram for loads applied on the left side of truck.
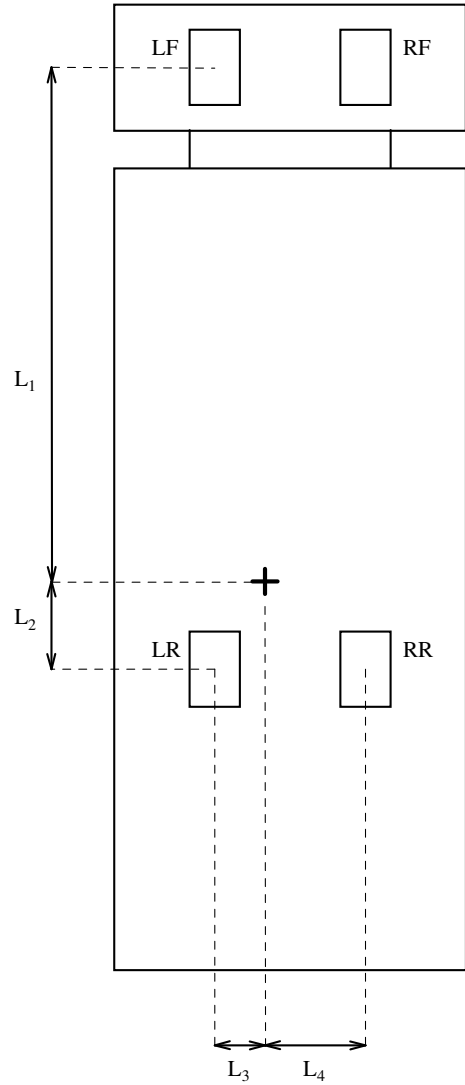

Fig. 10. Schematic diagram for distances measured from center of mass to truck suspensions.
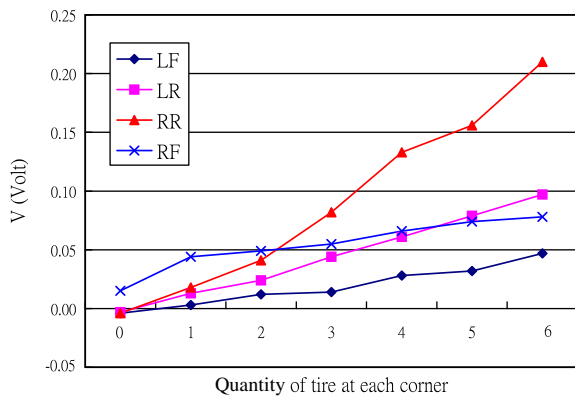

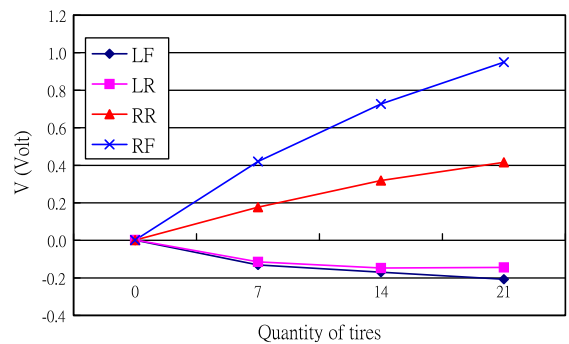Fig. 9. Experimental results of four-corner experiment.

Fig. 11. Results of right side experiment using a larger gain.

Table 1
Loads for each suspension

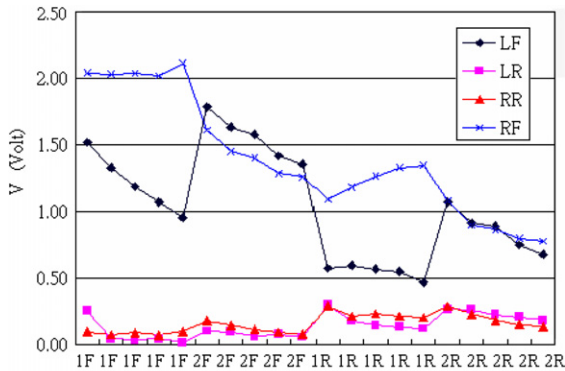|	LF (kg)	LR (kg)	RR (kg)	RF (kg)
Front (1407 kg)	376.631	323.370	323.370	376.631
Rear (1407 kg)	−257.428	957.428	957.428	−257.428
Left (1407 kg)	149.004	1600.996	−320.199	−29.800
Right (1407 kg)	−29.800	−320.199	1600.996	149.040
Corners (1608 kg)	62.771	737.229	737.229	62.771

Fig. 12. Experimental results of using a car as payload.

Table 2
Error percentages

Location	First day error (%)	Second day error (%)
Front	33	32
Rear	71	74
Front	−16	15
Rear	26	50
Front	−15	−03
Rear	27	27
Front	−22	−11
Rear	19	10
Front	−19	−22
Rear	13	−01

3. Neural network model

A neural network is a good tool to deal with system nonlinearity due to its learning and prediction capability. Therefore, a neural network is employed in this study to improve the accuracy of experimental results. The network adopted in this study is a "feedforward–backpropagation" model [7]. Simulation is executed by using a MATLAB [8] software on the basis of experimental data using truck tires and the car as payloads, respectively.

3.1. Simulation results of using car data

The model structure of this simulation is shown in Fig. 13, and the symbols are defined as follows:

(1) IW$\{k, 1\}$ is the weighting matrix of input, where $k, 1$ represents the linking source and destination of the matrix, respectively.
(2) LW$\{k, 1\}$ is the weighting matrix of hidden layers.
(3) b is the bias vector.
(4) $Sj, j = 1, 2, 3$, represents the neuron number of the associated hidden layer.

This model contains one nonlinear and two linear hidden layers, and the neuron numbers in each layer are 4, 4, 1, respectively. A log-sigmoid function [7] expressed by

$$\phi(v) = \frac{1}{1 + \exp(-cv)} \tag{15}$$

is used for the neuron to simulate nonlinearity, where v is a real number and c is an index number prescribed as 1 in this study. Output voltages of the four bridges depicted in Fig. 12 are used as inputs, and the corresponding weights are used as outputs. Among the 20 data sets, twelve data sets are used in training the neural networks, while the other
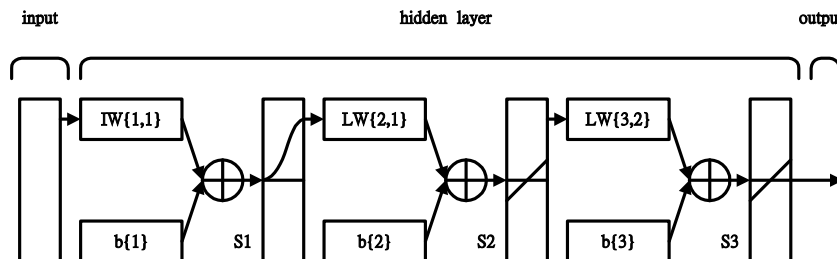

Fig. 13. Structure of neural network model.

eight are used for validation. The training is executed 600 times. Training results are shown in Fig. 14, where the mean-sum-square value of the error is 10^{-8}. Next, feed the eight validation data sets into the network to perform the simulation. The resultant outputs are all 1210 kg with error percentage less than 0.5%. The results show that the model is correct and the model has prediction capability.

3.2. Simulation results of using tire data

In this simulation, the resultant errors vary in a very wide range when the tire data are fed into the model used in Section 3.1. This implies that the neural network generated from car loading data cannot predict tire loading. One possible reason is that the center of gravity of the payload varies when tires are loaded one by one. Therefore, the training method should be modified by first pre-processing measurement data, network training, and finally recovering data in post-processing. The pre-processing and post-processing are respectively done by "prestd" and "poststd" functions that are provided by the MATLAB [8].

The pre-processing normalizes the averages and standard deviations of the input matrix and the goal matrix to be 0 and 1 correspondingly. The data
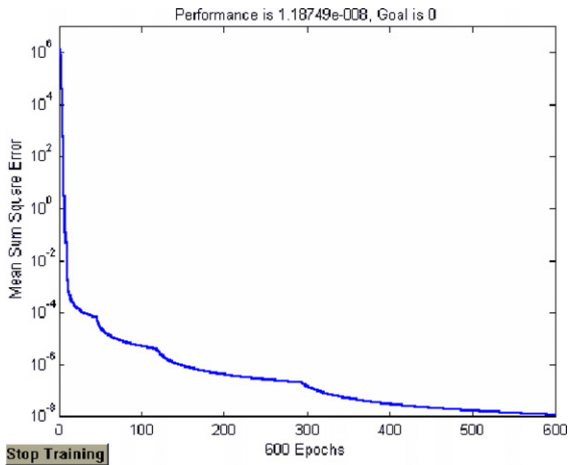

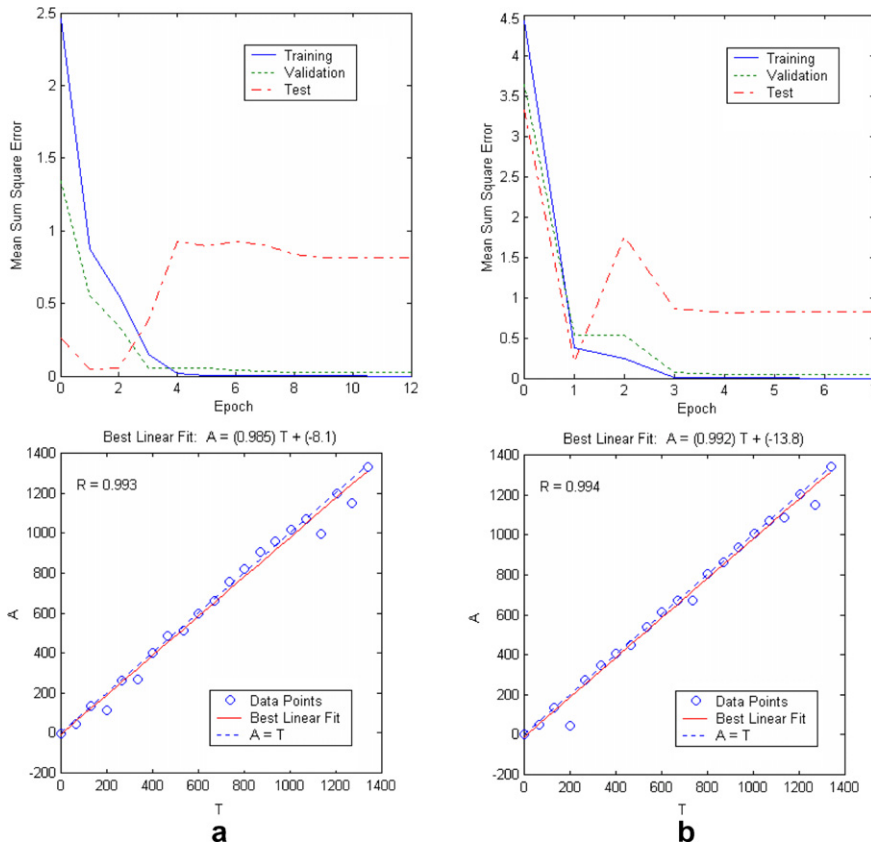Fig. 14. Training results of using car data.

Fig. 15. Simulation results for using tire data. (a) Front side; (b) rear side; (c) left side; (d) right side.
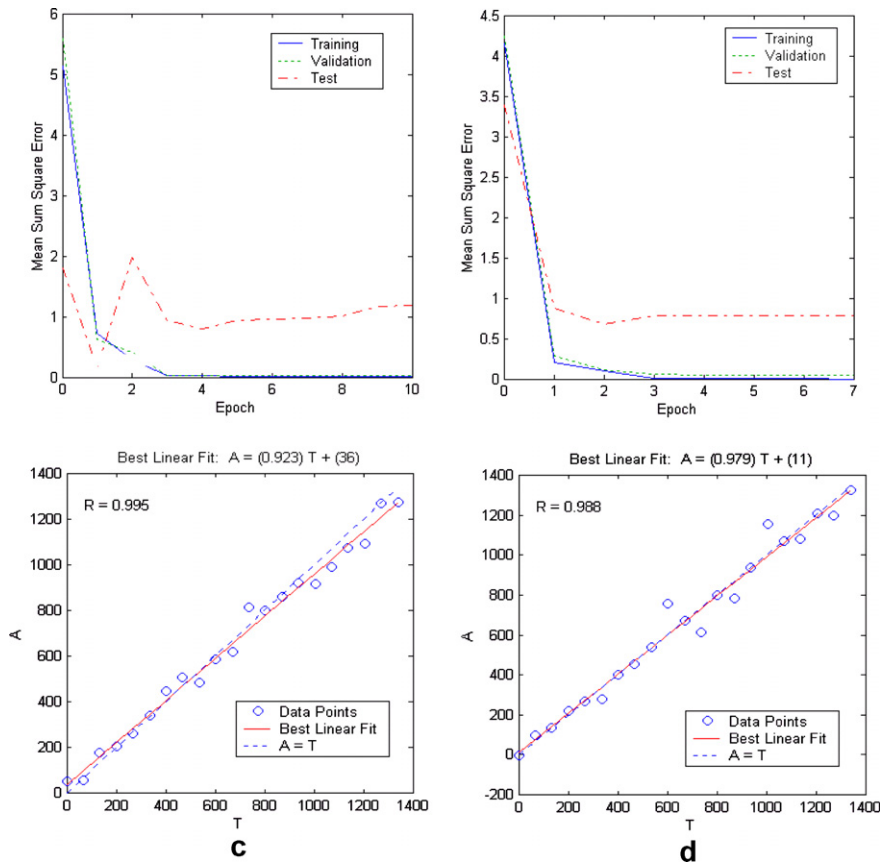
Fig. 15 (*continued*)

shown in Fig. 7 are used as inputs, which are divided into three categories: half of them as training data, a quarter of them as validation data, and the rest quarter testing data.

The network structure has also one nonlinear and two linear hidden layers, and the neuron numbers are 8, 4, 1, respectively. The input is a 4×21 matrix and the output matrix is 21×1. In the beginning of the training, both training errors and validation errors decrease; however, the validation errors increase once the network becomes over-fitting. An "over-fitting" for a neural network is a phenomenon in which errors of training data are reduced via training whereas errors of validation data become large [9]. By monitoring and controlling the validation errors, over-fitting can be abated. The final results are shown in Fig. 15, and the errors are summarized in Table 3. In Fig. 15, the first chart for each experiment shows mean-sum-square errors for each category of data, which verifies that the model has no over-fitting because both training error and validation error drop simultaneously.

Table 3
Simulation errors of using tire data

Tire-No.	Front side (%)	Rear side (%)	Left side (%)	Right side (%)
1	34.29	26.83	15.43	46.15
2	0.31	1.87	32.36	1.53
3	43.50	78.54	2.01	10.37
4	2.23	2.70	1.98	0.41
5	19.80	3.58	1.06	17.03
6	0.73	1.32	10.71	0.19
7	3.40	4.25	8.30	3.42
8	4.17	0.47	9.38	0.84
9	0.62	1.35	3.10	25.31
10	0.97	0.39	7.68	0.06
11	2.73	8.72	10.20	16.47
12	2.33	0.21	0.28	0.29
13	4.27	0.71	1.06	10.01
14	2.14	0.16	1.83	0.07
15	1.27	0.03	8.93	14.86
16	0.32	0.10	7.64	0.02
17	12.64	4.75	5.77	4.86
18	0.61	0.14	9.46	0.15
19	9.75	9.53	0.42	5.82
20	0.64	0.00	5.04	0.95
Average	7.34	7.28	7.13	7.94

The second chart for each experiment depicts results of linear regression where the horizontal axis, vertical axis, and the "R" are the goal matrix, output matrix, and the correlation coefficient, respectively. Correlation coefficients in Fig. 15 are all higher than 0.98, which means that simulation results are very close to the goal.

3.3. Simulation results of using both tires data and car data

The two models described in Sections 3.1 and 3.2 are used to deal with the associated data, respec-
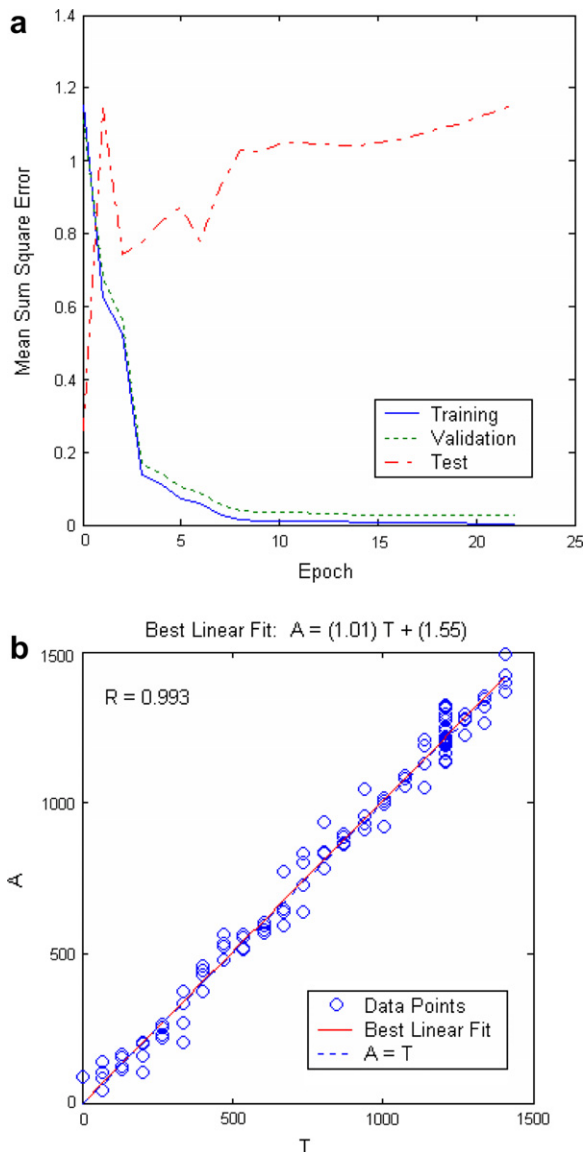

Fig. 16. Simulation results for using all the data.

tively. To process all the experimental data, a third model is designed. The model structure of this simulation has two nonlinear and two linear hidden layers. Neuron numbers in each layer are 16, 8, 4, and 1, respectively. Both data in Figs. 7 and 12 are used in this simulation. Hence, the input is a 4×104 matrix and the output matrix is 104×1. Simulation results are shown in Fig. 16. The average payload error is 8%.

4. Conclusions

A strain gage approach to payload measurement for a truck trailer has been performed in this study. Two kinds of objects were respectively employed as payloads: tires and a car. The payload is obtained by summing up measured loads in the four suspensions; however, resultant errors are quite large. One possible reason is that leaf springs did not recover in time to the original geometry before they were loaded again. Adjusting the amplifier gain in the bridge circuit can change the circuit sensitivity. A low gain reduces the result error whereas the output level is reduced at the same time.

A neural network has been developed by which three different models have been constructed to deal with data acquired from three experiments. Calculated payload errors are hence reduced. The largest error of the simulation occurs at the beginning of every experiment. It is caused by preloads that were not applied to leaf springs. In the neural network, the greater the number of neurons is employed, the less error it results in; nevertheless, the probability of encountering over-fitting is higher. The neural network model developed in this study indeed improves measurement result.

In future work, the whole system uncertainty will be verified under known or controlled conditions to determine the accuracy of the measuring system. Moreover, strong wind will shake truck trailers, which leads to flickering of displayed data, making data reading difficult. Therefore, the weather condition ought to be considered when performing experiments.

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