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Levenberg-Marquardt Backpropagation Training of Multilayer Neural Networks for State Estimation of A Safety Critical Cyber-Physical System

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***Abstract*— As an important safety critical cyber-physical system (CPS), the braking system is essential to the safe operation of the electric vehicle. Accurate estimation of the brake pressure is of great importance for automotive CPS design and control. In this paper, a novel probabilistic estimation method of brake pressure is developed for electrified vehicles based on multilayer Artificial Neural Networks (ANN) with Levenberg-Marquardt Backpropagation (LMBP) training algorithm. Firstly, the high-level architecture of the proposed multilayer ANN for brake pressure estimation is illustrated. Then, the standard backpropagation (BP) algorithm used for training of the feed-forward neural network (FFNN) is introduced. Based on the basic concept of backpropagation, a more efficient training algorithm of LMBP method is proposed. Next, real vehicle testing is carried out on a chassis dynamometer under standard driving cycles. Experimental data of the vehicle and the powertrain systems are collected, and feature vectors for FFNN training collection are selected. Finally, the developed multilayer ANN is trained using the measured vehicle data, and the performance of the brake pressure estimation is evaluated and compared with other available learning methods. Experimental results validate the feasibility and accuracy of the proposed ANN-based method for braking pressure estimation under real deceleration scenarios.**

***Index Terms*— Cyber-Physical System, Safety Critical System, Artificial Neural Networks, LMBP, Brake Pressure Estimation, Electric Vehicle.**

I. INTRODUCTION

CYBER physical systems, which are distributed, networked systems that fuse computational processes with the physical world exhibiting a multidisciplinary nature, have recently become a research focus [1-4]. As a typical application of CPS in green transportation, electric vehicles have been widely studied with different topics by researchers and engineers from academia, industry and governmental organizations [5-11]. In an electric vehicle (EV), the cyber world of control and communication, the physical plant of electric powertrain, the human driver, and the driving environment, are tightly coupled and dynamically interacted, determining the overall system's performance jointly [12]. These complex subsystems with multi-disciplinary interactions, strong uncertainties, and hard nonlinearities make the estimation, control and optimization of electric vehicles very difficult [13]. Thus, there are still a number of fundamental issues and critical challenges varying in their importance from convenience to safety of EV remained open [14-17].

Among all those concerns in EV CPS, a key one is safety. Safety critical systems are those ones whose failure or malfunction may result in serious injury or severe damage to people, equipment, or environment [18]. As one of the most important safety critical systems in EV, the correct functioning of braking system is essential to the safe operation of the vehicle [19]. There are a variety of safety standards, control algorithms, and developed devices helping guarantee braking safety for current EVs. However, with increasing degrees of electrification, control authority and autonomy of automotive CPS, safety critical functions of braking system are also required to evolve to keep pace [20].

In the braking system of a passenger car, the braking torque is generated by the hydraulic pressure applied in the brake cylinder. Thus, the accurate measurement of the brake pressure through a pressure sensor is of great importance for various braking control functions and chassis stability logics. However, failures of the brake pressure measurement, which may be caused by software discrepancies or hardware problems, could result in vehicle's critical safety issues. Thus, high-precision estimation of brake pressure become a hot research area in automotive CPS design and control. Moreover, in order to handle the trade-offs between performance and cost, sensor-less observation is required. This makes the study of brake pressure estimation highly motivated.

Based on advanced theories and algorithms from the aspect of control engineering, observation methods of braking pressure for vehicles have been investigated by researchers worldwide. In [21], a recursive least square algorithm for estimation of brake cylinder pressure was proposed based on the pressure response characteristics of anti-lock braking

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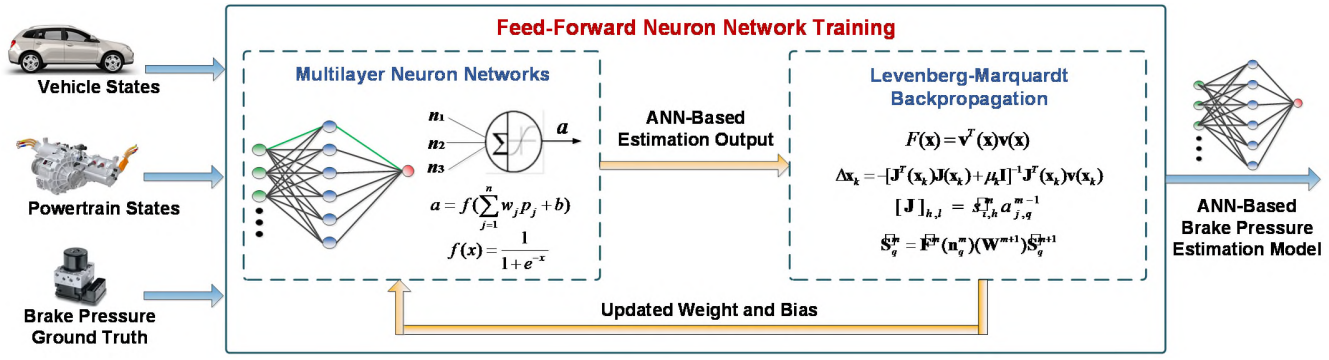


Fig. 1 High-level architecture of the proposed brake pressure estimation algorithm based on multilayer Artificial Neural Networks.

system (ABS). In [22], an extended-kalman-filter-based estimation algorithm was developed considering hydraulic model and tyre dynamics. In [23], an algorithm for online observation of brake pressure was designed through a developed inverse model, and the algorithm was verified in the vehicle's electronic stability program. In [24], the models of brake pressure increase, decrease and hold are proposed, respectively, by using the experimental data. And the models can be used for fast online observation of hydraulic brake pressure. In [25], a brake pressure estimation algorithm was proposed for ABS considering the hydraulic fluid characteristics. In [26], the estimation algorithm was performed by calculating the volume of fluid flowing through the valve. The amount of fluid is a function of the pressure differential across the valve and the actuation time of the valve. Nevertheless, the existing research on brake pressure estimation was mainly investigated from the perspective of control engineering, and an approach with the probabilistic method, such as machine learning, has rarely been seen.

In this paper, an Artificial-Neural-Network-based estimation method is studied for accurately observing the brake pressure of an electric passenger car. The main contribution of this work lies in the following aspects: 1) an ANN-based machine learning framework is proposed to quantitatively estimate the brake pressure of an EV; 2) The proposed approach is implemented with experimental data obtained via vehicle testing, and compared with other methods; 3) The proposed approaches has a great potential to achieve a sensorless design of the braking control system, removing the brake pressure sensor existing in the current products and largely reducing the cost of the system. Moreover, it also provides an additional redundancy for the safety-critical braking functions.

The rest of this paper is organized as follows. Section II describes the high-level architecture of the proposed multilayer ANN for brake pressure estimation. Section III briefly introduces the standard backpropagation algorithm and illustrate the notations and basic concepts demanded in the Levenberg-Marquardt algorithm. Section IV presents details of the application of the LMBP method to training the feed-forward neural networks. In Section V, experiment implementations including feature selection, data collection and preprocessing are presented. Section VI reports the experimental results of the proposed brake pressure estimation algorithm including performance comparison to other approaches. Finally, conclusions are made in Section VII.

II. Multilayer Artificial Neural Networks Architecture

In order to achieve the objective of brake pressure estimation, multilayer artificial neural networks are firstly constructed with the input of vehicle and powertrain states. Details of the high-level system architecture and structure of the component are described in this section.

A. System Architecture

The system architecture with proposed methodology is shown in Fig. 1. The multilayer artificial neural network receives state variables of the vehicle and the electric powertrain system as inputs, and then yields the estimation of the brake pressure through the activation function. The Levenberg-Marquardt Backpropagation algorithm is then operated with the performance function, which is a function of the ANN-based estimation and the ground truth of brake pressure. The weight and bias variables are adjusted according to Levenberg-Marquardt method, and the backpropagation algorithm is used to calculate the Jacobian matrix of the performance function with respect to the weight and bias variables. With updated weights and biases, the ANN further estimates the brake pressure at the next time step. On the basis of the above iterative processes, the ANN-based brake pressure estimation model is well trained. The detailed method and algorithms are introduced in the following subsection.

B. Multilayer Feed-Forward Neural Network

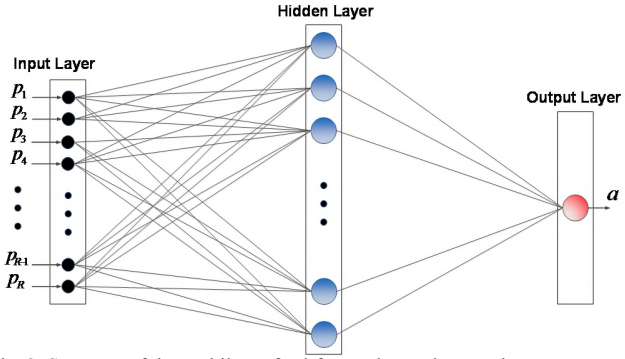


Fig. 2 Structure of the multilayer feed-forward neural network.

In this work, a multilayer feed-forward neural network is chosen to estimate brake pressure. A FFNN is composed of one

input layer, one or more hidden layers and one output layer. Since a neural network with one hidden layer has the capability to handle most of the complex functions, in this work the FFNN with one hidden layer is constructed. Fig. 2 shows the structure of a multilayer FFNN with one hidden layer.

The basic element of a FFNN is the neuron, which is a logical-mathematical model that seeks to simulate the behavior and functions of a biological neuron [27]. Fig. 3 shows the schematic structure of a neuron. Typically, a neuron has more than one input. The elements in the input vector $\mathbf{p} = [p_1, p_2, \mathrm{K}, p_R]$ are weighted by elements $w_1, w_2, \mathrm{K}, w_j$ of the weight matrix $\mathbf{W}$ respectively.

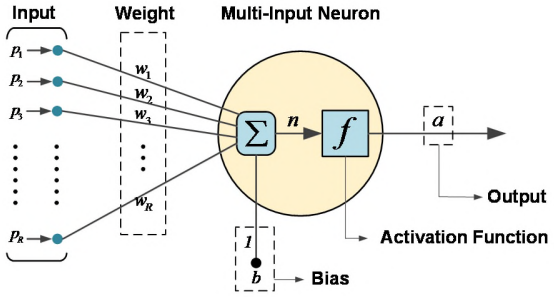


Fig. 3 Structure of the multi-input neuron.

The neuron has a bias b, which is summed with the weighted inputs to form the net input n, which can be expressed by

$$n = \sum_{j=1}^{R} w_j p_j + b = \mathbf{W}\mathbf{p} + b \tag{1}$$

Then the net input n passes through an active function f, which generates the neuron output a.

$$a = f(n) \tag{2}$$

In this study, the log-sigmoid activation function is adopted. It can be given by the following expression:

$$f(x) = \frac{1}{1+e^{-x}} \tag{3}$$

Thus, the multi-input FFNN in Fig. 2 implements the following equation

$$a^2 = f^2\left(\sum_{i=1}^{S} w_{1,i}^2 f^1\left(\sum_{j=1}^{R} w_{i,j}^1 p_j + b_i^1\right) + b^2\right) \tag{4}$$

where a^2 denotes the output of the overall networks. R is the number of inputs, S is the number of neurons in the hidden layer, and p_j indicates the jth input. f^1 and f^2 are the activation functions of the hidden layer and output layer, respectively. b_i^1 represents the bias of the ith neuron in the hidden layer, and b^2 is the bias of the neuron in the output layer. $w_{i,j}^1$ represents the weight connecting the jth input and the ith neuron of the hidden layer, and $w_{1,i}^2$ represents the weight connecting the ith source of the hidden layer to the output layer neuron.

III. Standard Backpropagation Algorithm

In order to train the established FFNN, the backpropagation algorithm can be utilized [28]. Considering a multilayer feedforward neural network, such as the one with three-layer shown in Fig. 2, its operation can be described using the following equation:

$$\mathbf{a}^{m+1} = \mathbf{f}^{m+1}(\mathbf{W}^{m+1}\mathbf{a}^m + \mathbf{b}^{m+1}) \tag{5}$$

where $\mathbf{a}^m$ and $\mathbf{a}^{m+1}$ are the outputs of the m-th and (m+1)-th layers of the networks, respectively. $\mathbf{b}^{m+1}$ is the bias vector of (m+1)-th layers of the networks. $m = 0, 1, ..., M-1$, where M is the number of layers of the neural network. The neurons of the first layer obtain inputs:

$$\mathbf{a}^0 = \mathbf{p} \tag{6}$$

Eq. (6) provides the initial condition for Eq. (5). The outputs of the neurons in the last layer can be seen as the overall networks' outputs:

$$\mathbf{a} = \mathbf{a}^M \tag{7}$$

The task is to train the network with associations between a specified set of input-output pairs $\{(\mathbf{p}_1, \mathbf{t}_1), (\mathbf{p}_2, \mathbf{t}_2), ..., (\mathbf{p}_Q, \mathbf{t}_Q)\}$, where $\mathbf{p}_q$ is an input to the network, and $\mathbf{t}_q$ is the corresponding target output. As each input is applied to the network, the network output is compared to the target.

The backpropagation algorithm uses mean square error as the performance index, which is to be minimized by adjusting the network parameters, as shown in Eq. (8).

$$F(\mathbf{x}) = E[\mathbf{e}^T\mathbf{e}] = E[(\mathbf{t}-\mathbf{a})^T(\mathbf{t}-\mathbf{a})] \tag{8}$$

where $\mathbf{x}$ is the vector matrix of network weights and biases. Using the approximate steepest descent rule, the performance index $F(\mathbf{x})$ can be approximated by

$$\hat{F}(\mathbf{x}) = (\mathbf{t}(k)-\mathbf{a}(k))^T(\mathbf{t}(k)-\mathbf{a}(k)) = \mathbf{e}^T(k)\mathbf{e}(k) \tag{9}$$

where the expectation of the squared error in Eq. (8) has been replaced by the squared error at iteration step k.

The steepest descent algorithm for the approximate mean square error is

$$w_{i,j}^m(k+1) = w_{i,j}^m(k) - \alpha\frac{\partial\hat{F}}{\partial w_{i,j}^m} \tag{10}$$

$$b_i^m(k+1) = b_i^m(k) - \alpha\frac{\partial\hat{F}}{\partial b_i^m} \tag{11}$$

where α is the learning rate.

Based on the chain rule, the derivatives in Eq. (10) and Eq. (11) can be calculated as:

$$\frac{\partial\hat{F}}{\partial w_{i,j}^m} = \frac{\partial\hat{F}}{\partial n_i^m}\cdot\frac{\partial n_i^m}{\partial w_{i,j}^m}, \quad \frac{\partial\hat{F}}{\partial b_i^m} = \frac{\partial\hat{F}}{\partial n_i^m}\cdot\frac{\partial n_i^m}{\partial b_i^m} \tag{12}$$

We now define s_i^m as the sensitivity of $\hat{F}$ to changes in the ith element of the net input at layer m.

$$s_i^m \equiv \frac{\partial\hat{F}}{\partial n_i^m} \tag{13}$$

Using the defined sensitivity, then the derivatives in Eq. (12) can be simplified as

$$\frac{\partial\hat{F}}{\partial w_{i,j}^m} = s_i^m a_j^{m-1} \tag{14}$$

$$\frac{\partial \hat{F}}{\partial b_i^m} = s_i^m \tag{15}$$

Then the approximate steepest descent algorithm can be rewritten in matrix form as:

$$\mathbf{W}^m(k+1) = \mathbf{W}^m(k) - \alpha \mathbf{s}^m (\mathbf{a}^{m-1})^T \tag{16}$$

$$\mathbf{b}^m(k+1) = \mathbf{b}^m(k) - \alpha \mathbf{s}^m \tag{17}$$

where

$$\mathbf{s}^m \equiv \frac{\partial \hat{F}}{\partial \mathbf{n}^m} = [\frac{\partial \hat{F}}{\partial n_1^m}, \frac{\partial \hat{F}}{\partial n_2^m}, ..., \frac{\partial \hat{F}}{\partial n_{S^m}^m}]^T \tag{18}$$

To derive the recurrence relationship for the sensitivities, the following Jacobian matrix is utilized.

$$\frac{\partial \mathbf{n}^{m+1}}{\partial \mathbf{n}^m} \equiv \begin{bmatrix} \frac{\partial n_1^{m+1}}{\partial n_1^m} & \frac{\partial n_1^{m+1}}{\partial n_2^m} & \text{L} & \frac{\partial n_1^{m+1}}{\partial n_{S^m}^m} \\ \frac{\partial n_2^{m+1}}{\partial n_1^m} & \frac{\partial n_2^{m+1}}{\partial n_2^m} & \text{L} & \frac{\partial n_2^{m+1}}{\partial n_{S^m}^m} \\ \text{M} & \text{M} & & \text{M} \\ \frac{\partial n_{S^{m+1}}^{m+1}}{\partial n_1^m} & \frac{\partial n_{S^{m+1}}^{m+1}}{\partial n_2^m} & \text{L} & \frac{\partial n_{S^{m+1}}^{m+1}}{\partial n_{S^m}^m} \end{bmatrix} \tag{19}$$

Consider the i, j element in the matrix:

$$\frac{\partial n_1^{m+1}}{\partial n_1^m} = w_{i,j}^{m+1} \frac{\partial a_j^m}{\partial n_j^m} = w_{i,j}^{m+1} \dot{f}^m(n_j^m) \tag{20}$$

Thus, the Jacobian matrix can be rewritten as

$$\frac{\partial \mathbf{n}^{m+1}}{\partial \mathbf{n}^m} = \mathbf{W}^{m+1} \dot{\mathbf{F}}^m(\mathbf{n}^m) \tag{21}$$

where

$$\dot{\mathbf{F}}^m(\mathbf{n}^m) = \begin{bmatrix} \dot{f}^m(n_1^m) & 0 & \text{K} & 0 \\ 0 & \dot{f}^m(n_2^m) & & 0 \\ \text{M} & \text{M} & & \text{M} \\ 0 & 0 & \text{K} & \dot{f}^m(n_{S^m}^m) \end{bmatrix} \tag{22}$$

Then the recurrence relation for the sensitivity can be obtained by using the chain rule:

$$\begin{aligned} \mathbf{s}^m &= \frac{\partial \hat{F}}{\partial \mathbf{n}^m} = \left(\frac{\partial \mathbf{n}^{m+1}}{\partial \mathbf{n}^m} \right)^T \frac{\partial \hat{F}}{\partial \mathbf{n}^{m+1}} \\ &= \dot{\mathbf{F}}^m(\mathbf{n}^m)(\mathbf{W}^{m+1})^T \mathbf{s}^{m+1} \end{aligned} \tag{23}$$

This recurrence relation is initialized at the final layer as

$$\begin{aligned} s_i^M &= \frac{\partial \hat{F}}{\partial n_i^M} = \frac{\partial ((\mathbf{t}-\mathbf{a})^T(\mathbf{t}-\mathbf{a}))}{\partial n_i^M} = \frac{\partial \sum_{j=1}^{S^M} (t_j - a_j)^2}{\partial n_i^M} \\ &= -2(t_i - a_i) \frac{\partial a_i}{\partial n_i^M} = -2(t_i - a_i) \dot{f}^m(n_i^m) \end{aligned} \tag{24}$$

Thus the recurrence relation of the sensitivity matrix can be expressed as

$$\mathbf{s}^M = -2\dot{\mathbf{F}}^M(\mathbf{n}^M)(\mathbf{t}-\mathbf{a}) \tag{25}$$

The overall BP learning algorithm is now finalized and can be summarized as the following steps: 1) firstly, propagate the input forward through the network; 2) secondly, propagate the sensitivities backward through the network from the last layer to the first layer; 3) finally, update the weights and biases using the approximate steepest descent rule.

IV. Levenberg-Marquardt Backpropagation

While backpropagation is a steepest descent algorithm, the Levenberg-Marquardt algorithm is derived from Newton's method that was designed for minimizing functions that are sums of squares of nonlinear functions [29, 30].

Newton's method for optimizing a performance index $F(\mathbf{x})$ is

$$\mathbf{x}_{k+1} = \mathbf{x}_k - \mathbf{A}_k^{-1} \mathbf{g}_k \tag{26}$$

$$\mathbf{A}_k \equiv \nabla^2 F(\mathbf{x})|_{\mathbf{x}=\mathbf{x}_k} \tag{27}$$

$$\mathbf{g}_k \equiv \nabla F(\mathbf{x})|_{\mathbf{x}=\mathbf{x}_k} \tag{28}$$

where $\nabla^2 F(\mathbf{x})$ is the Hessian matrix and $\nabla F(\mathbf{x})$ is the gradient.

Assume that $F(\mathbf{x})$ is a sum of squares function:

$$F(\mathbf{x}) = \sum_{i=1}^{N} v_i^2(\mathbf{x}) = \mathbf{v}^T(\mathbf{x})\mathbf{v}(\mathbf{x}) \tag{29}$$

then the gradient and Hessian matrix are

$$\nabla F(\mathbf{x}) = 2\mathbf{J}^T(\mathbf{x})\mathbf{v}(\mathbf{x}) \tag{30}$$

$$\nabla^2 F(\mathbf{x}) = 2\mathbf{J}^T(\mathbf{x})\mathbf{J}(\mathbf{x}) + 2\mathbf{S}(\mathbf{x}) \tag{31}$$

where $\mathbf{J}(\mathbf{x})$ is the Jacobian matrix

$$\mathbf{J}(\mathbf{x}) = \begin{bmatrix} \frac{\partial v_1(\mathbf{x})}{\partial x_1} & \frac{\partial v_1(\mathbf{x})}{\partial x_2} & \text{L} & \frac{\partial v_1(\mathbf{x})}{\partial x_n} \\ \frac{\partial v_2(\mathbf{x})}{\partial x_1} & \frac{\partial v_2(\mathbf{x})}{\partial x_2} & \text{L} & \frac{\partial v_2(\mathbf{x})}{\partial x_n} \\ \text{M} & \text{M} & & \text{M} \\ \frac{\partial v_N(\mathbf{x})}{\partial x_1} & \frac{\partial v_N(\mathbf{x})}{\partial x_2} & \text{L} & \frac{\partial v_N(\mathbf{x})}{\partial x_n} \end{bmatrix} \tag{32}$$

and

$$\mathbf{S}(\mathbf{x}) = \sum_{i=1}^{N} v_i(\mathbf{x}) \nabla^2 v_i(\mathbf{x}) \tag{33}$$

If $\mathbf{S}(\mathbf{x})$ is assumed to be small then the Hessian matrix can be approximated as

$$\nabla^2 F(\mathbf{x}) \cong 2\mathbf{J}^T(\mathbf{x})\mathbf{J}(\mathbf{x}) \tag{34}$$

Substituting Eq. (30) and Eq. (34) into Eq. (26), we achieve the Gauss-Newton method as:

$$\Delta \mathbf{x}_k = -[\mathbf{J}^T(\mathbf{x}_k)\mathbf{J}(\mathbf{x}_k)]^{-1}\mathbf{J}^T(\mathbf{x}_k)\mathbf{v}(\mathbf{x}_k) \tag{35}$$

One problem with the Gauss-Newton method is that the matrix may not be invertible. This can be overcome by using the following modification to the approximate Hessian matrix:

$$\mathbf{G} = \mathbf{H} + \mu\mathbf{I} \tag{36}$$

This leads to the Levenberg-Marquardt algorithm [31]:

$$\Delta \mathbf{x}_k = -[\mathbf{J}^T(\mathbf{x}_k)\mathbf{J}(\mathbf{x}_k) + \mu_k\mathbf{I}]^{-1}\mathbf{J}^T(\mathbf{x}_k)\mathbf{v}(\mathbf{x}_k) \tag{37}$$

Using this gradient direction, and recompute the approximated performance index. If a smaller value is yield, then the procedure is continued with the μ_k divided by some factor $\vartheta > 1$. If the value of the performance index is not reduced, then μ_k is multiplied by ϑ for the next iteration step.

The key step in this algorithm is the computation of the Jacobian matrix. The elements of the error vector and the parameter vector in the Jacobian matrix (32) can be expressed as

$$\mathbf{v}^T = [v_1 \;\; v_2 \;\; \mathrm{K} \;\; v_N] = [e_{1,1} \;\; e_{2,1} \;\; \mathrm{K} \;\; e_{S^M,1} \;\; e_{1,2} \mathrm{K} \;\; e_{S^M,Q}] \tag{38}$$

$$\mathbf{x}^T = [x_1 \;\; x_2 \;\; \mathrm{K} \;\; x_N] = [w^1_{1,1} \;\; w^1_{1,2} \;\; \mathrm{K} \;\; w^1_{S^1,R} \;\; b^1_1 \mathrm{K} \;\; b^1_{S^1} \;\; w^2_{1,1} \mathrm{K} \;\; b^M_{S^M}] \tag{39}$$

where the subscript N satisfies:

$$N = Q \times S^M \tag{40}$$

and the subscript n in the Jacobian matrix satisfies:

$$n = S^1(R+1) + S^2(S^1+1) + \mathrm{L} + S^M(S^{M-1}+1) \tag{41}$$

Making these substitutions into Eq. (32), then the Jacobian matrix for multilayer network training can be expressed as

$$\mathbf{J}(\mathbf{x}) = \begin{bmatrix} \frac{\partial e_{1,1}}{\partial w^1_{1,1}} & \frac{\partial e_{1,1}}{\partial w^1_{1,2}} & \mathrm{L} & \frac{\partial e_{1,1}}{\partial w^1_{S^1,R}} & \frac{\partial e_{1,1}}{\partial b^1_1} & \mathrm{L} \\ \frac{\partial e_{2,1}}{\partial w^1_{1,1}} & \frac{\partial e_{2,1}}{\partial w^1_{1,2}} & \mathrm{L} & \frac{\partial e_{2,1}}{\partial w^1_{S^1,R}} & \frac{\partial e_{2,1}}{\partial b^1_1} & \mathrm{L} \\ \mathrm{M} & \mathrm{M} & & \mathrm{M} & \mathrm{M} & \\ \frac{\partial e_{S^M,1}}{\partial w^1_{1,1}} & \frac{\partial e_{S^M,1}}{\partial w^1_{1,2}} & \mathrm{L} & \frac{\partial e_{S^M,1}}{\partial w^1_{S^1,R}} & \frac{\partial e_{S^M,1}}{\partial b^1_1} & \mathrm{L} \\ \frac{\partial e_{1,2}}{\partial w^1_{1,1}} & \frac{\partial e_{1,2}}{\partial w^1_{1,2}} & \mathrm{L} & \frac{\partial e_{1,2}}{\partial w^1_{S^1,R}} & \frac{\partial e_{1,2}}{\partial b^1_1} & \mathrm{L} \\ \mathrm{M} & \mathrm{M} & & \mathrm{M} & \mathrm{M} & \end{bmatrix} \tag{42}$$

In standard backpropagation algorithm, the terms in the Jacobian matrix is calculated as

$$\frac{\partial \hat{F}(\mathbf{x})}{\partial x_l} = \frac{\partial \mathbf{e}_q^T \mathbf{e}_q}{\partial x_l} \tag{43}$$

For the elements of the Jacobian matrix, the terms can be calculated by

$$[\mathbf{J}]_{h,l} = \frac{\partial v_h}{\partial x_l} = \frac{\partial e_{k,q}}{\partial w_{i,j}} \tag{44}$$

Thus in this modified Levenberg-Marquardt algorithm, we compute the derivatives of the errors, instead of the derivatives of the squared errors as adopted in standard backpropagation.

Using the concept of sensitivities in the standard backpropagation process, here we define a new Marquardt sensitivity as

$$s^m_{i,h} \equiv \frac{\partial v_h}{\partial n^m_{i,q}} = \frac{\partial e_{k,q}}{\partial n^m_{i,q}} \tag{45}$$

where $h = (q-1)S^M + k$.

Using the Marquardt sensitivity with backpropagation recurrence relationship, the elements of the Jacobian can be further calculated by

$$[\mathbf{J}]_{h,l} = \frac{\partial e_{k,q}}{\partial w^m_{i,j}} = \frac{\partial e_{k,q}}{\partial n^m_{i,q}} \frac{\partial n^m_{i,q}}{\partial w^m_{i,j}} = s^m_{i,h} a^{m-1}_{j,q} \tag{46}$$

if x_l is a bias,

$$[\mathbf{J}]_{h,l} = \frac{\partial e_{k,q}}{\partial b^m_i} = \frac{\partial e_{k,q}}{\partial n^m_{i,q}} \frac{\partial n^m_{i,q}}{\partial b^m_i} = s^m_{i,h} \tag{47}$$

The Marquardt sensitivities can be computed using the same recurrence relations as the one used in the standard BP method, with one modification at the final layer. The Marquardt sensitivities at the last layer can be given by

$$\begin{aligned} s^M_{i,h} &= \frac{\partial e_{k,q}}{\partial n^M_{i,q}} = \frac{\partial (t_{k,q} - a^M_{k,q})}{\partial n^M_{i,q}} = -\frac{\partial a^M_{k,q}}{\partial n^M_{i,q}} \\ &= \begin{cases} -\dot{f}^M(n^M_{l,q}) & \text{for } i = k \\ 0 & \text{for } i \neq k \end{cases} \end{aligned} \tag{48}$$

After applying the $\mathbf{p}_q$ to the network and computing the corresponding output $\mathbf{a}^M_q$, the LMBP algorithm can be initialized by

$$\tilde{\mathbf{S}}^M_q = -\dot{\mathbf{F}}^M(\mathbf{n}^M_q) \tag{49}$$

Each column of the matrix should be backpropagated through the network so as to generate one row of the Jacobian matrix. The columns can also be backpropagated together using

$$\tilde{\mathbf{S}}^m_q = \dot{\mathbf{F}}^m(\mathbf{n}^m_q)(\mathbf{W}^{m+1})\tilde{\mathbf{S}}^{m+1}_q \tag{50}$$

The entire Marquardt sensitivity matrices for the overall layers are then obtained by the following augmentation

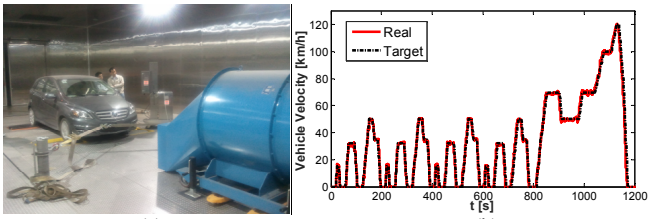
$$\tilde{\mathbf{S}}^m = \left[\tilde{\mathbf{S}}^m_1 \,|\, \tilde{\mathbf{S}}^m_2 \,|\, \mathrm{K} \,|\, \tilde{\mathbf{S}}^m_Q\right] \tag{51}$$

V. Experimental Testing and Data Collection

In order to train the FFNN model with the LMBP algorithm proposed above and validate its effectiveness for brake pressure estimation, real vehicle driving data is needed. Thus, experiments using an electric passenger car are carried out on a chassis dynamometer. The testing vehicle together with the testing scenarios, selected feature vectors, data collection and data pre-processing are described as follows.

A. Testing Vehicle and Scenario

The experiment is implemented on a chassis dynamometer with an electric passenger car, as shown in Fig. 4(a). The utilized electric vehicle is driven by a permanent-magnet synchronous motor, which is able to work in either driving or regenerating mode. The battery pack is connected to the electric motor via D.C. bus, releasing or absorbing power during driving and regenerative braking processes, respectively. Key parameters of the test vehicle are presented in Table 1.



(a) (b)

Fig. 4. (a) The testing vehicle operating on a chassis dynamometer; (b) Speed profile of the NEDC driving cycle.

TABLE 1
KEY PARAMETERS OF THE ELECTRIC VEHICLE.

Parameter	Value	Unit
Total vehicle mass	1360	kg
Wheel base	2.50	m
Frontal area	2.40	m^2
Nominal radius of tyre	0.295	m
Coefficient of air resistance	0.32	—
Motor peak power	45	kW
Motor maximum torque	144	Nm
Motor maximum speed	9000	rpm
Battery voltage	326	V
Battery capacity	66	Ah

To set up the testing scenario on a chassis dynamometer, standard driving cycles can be utilized. In this study, the New European Drive Cycle (NEDC) which consists of four repeated ECE-15 urban driving cycles and one Extra Urban Driving Cycle (EUDC) is adopted [32]. As Fig. 4(b) shows, the four successive ECE-15 driving cycles in the first section of the NEDC represent urban driving with low operating speed while the second section, i.e. the EUDC driving cycle, indicates a highway driving scenario with the vehicle speed up to 120 km/h.

B. Data Collection and Processing

Vehicle data and powertrain states on CAN bus are collected with a sampling frequency of 100 Hz. Finally, experimental data of 6327 seconds containing six NEDC driving cycles in total are recorded. The vehicle speed and brake pressure of the collected testing data during the four successive ECE-15 driving cycles are presented in Fig. 5.

In order to achieve a better training performance of the FFNN model with machine learning methods, the raw experimental data are smoothed at first using the following equation:

$$d_t = \frac{1}{N}\sum_{n}^{N} d_{tn} \tag{52}$$

where d_t is the value of a signal at time t, d_{tn} is the n-th sampled value of signal d at time step t, and N is the total amount of samples within each second.

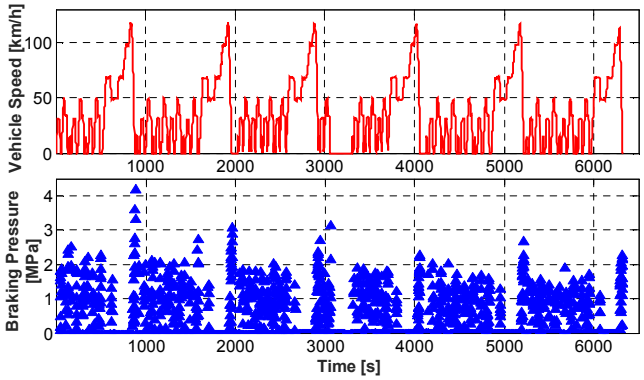


Fig. 5 Collected data of the vehicle speed and corresponding brake pressure.

Then, in order to eliminate the effect brought by different units of signals utilized, the input signals are scaled to be in the range of 0 to 1.

C. Feature Selection and Model Training

In this work, the important vehicle and powertrain state variables are selected for the training of the multilayer ANN model for brake pressure estimation, while the real value of the brake pressure is utilized as a ground truth during the training process. When the electric vehicle is decelerating, the electric motor operates as a generator, recapturing vehicle's kinetic energy. During this period, the values of the motor and battery current change from positive to negative, indicating that the battery is charged by regenerative braking energy. Thus, apart from the vehicle states, the signals of motor speed and torque, battery current and voltage, state of charge (SoC) are also chosen as features, i.e. the input vector of the FFNN. The data of some of the selected feature variables during one driving cycle are shown in Fig. 6.

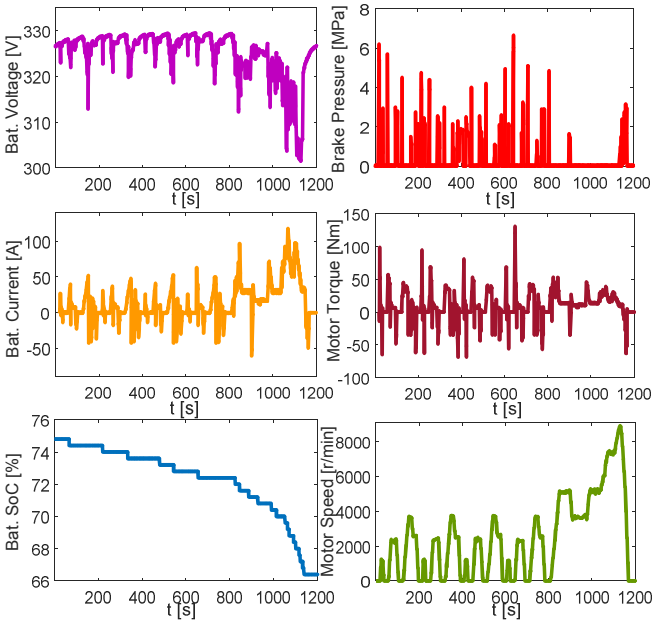


Fig. 6 Experimental data of selected features during one driving cycle.

Besides, statistical information, including the mean value, maximum value, and standard deviation (STD) of some of the vehicle states in the past few seconds are also adopted in this

work. The features used for model training are listed below in Table 2.

TABLE 2
SELECTED FEATURES FOR FFNN MODEL TRAINING

No.	Signal	Unit
1	Vehicle Velocity	*km/h*
2	Mean Value of Velocity	*km/h*
3	STD of Velocity	*km/h*
4	Maximum Value of Velocity	*km/h*
5	Vehicle Acceleration	m/s^2
6	Motor Speed	*rad/s*
7	Motor Torque	Nm
8	Battery Current	A
9	Battery Voltage	V
10	Battery SoC	%
11	Gradient of Bat. Voltage	V/s
12	Gradient of Bat. Current	A/s

After determining the feature vectors, the regression model of the FFNN is trained. To modulate and evaluate the model performance, the *K*-fold cross validation approach is adopted [33]. In this method, among the *K* folds divided, (*K*-1) ones are utilized to train the model, and the rest one fold is adopted for testing. Thus, the overall recorded data are divided into two sets, namely the training set and the testing one. The testing set, which is used for model validation, contains 1400 samples chosen randomly from the raw data, and rest of the data are allocated to the training set. The final evaluation of the model performance is carried out based on the *K* test results. In this work, the value of *K* is set as 5. Then, with the 5-fold cross validation, the constructed FFNN is trained using the fast LMBP algorithm developed in Section IV. Some key parameter of FFNN are illustrated below.

TABLE 3
KEY PARAMETERS OF THE FFNN MODEL

Parameter	Value
Maximum number of epochs to train	1000
Performance goal	0
Maximum validation failures	6
Minimum performance gradient	$1e^{-7}$
Initial μ	0.001
μ decrease factor	0.1
μ increase factor	10
Maximum μ	$1e^{10}$
Epochs between displays	25
Maximum time to train in seconds	Infinite

VI. EXPERIMENT RESULTS AND DISCUSSIONS

In this section, results of the estimated ANN-based brake pressure with LMBP learning algorithm are presented and discussed. The algorithms are implemented in a computer with the MATLAB 2017a platform. The processor of the computer is an Intel Core i7-4710MQ CPU which supports 4 cores and 8 threads parallel computing, while the RAM equipped is a 32G one. The time consuming for the FFNN training varies with the number of the hidden neurons selected. In this study, since the range of hidden neurons number is from 10 to 100, thus the training time for FFNN varies from 0.6s to 10s, and the average training time cost for the FFNN with 70 neurons is 3.4s.

A. Results of the ANN-based Braking Pressure Estimation

To quantitatively evaluate the estimation performance, two commonly used indicies, namely the coefficient of determination R^2 and the root-mean-square-error (RMSE), are adopted. The definitions of the R^2 and RMSE are presented as follows. Suppose the reference data is $T = \{t_1 \text{K } t_N\}$, and the predicted value is $Y = \{y_1 \text{K } y_N\}$. Then R^2 can be calculated as:

$$R^2 = 1 - \frac{E_{res}}{E_{tot}} \tag{53}$$

$$E_{res} = \sum_i^N (t_i - y_i)^2 \tag{54}$$

$$E_{tot} = \sum_i^N (t_i - \bar{T})^2 \tag{55}$$

where E_{res} is the residual sum of square, E_{tot} is the total sum of square, and $\bar{T}$ is the mean value of the reference data.

The RMSE can be obtained by:

$$RMSE = \sqrt{\frac{\sum_i^N (t_i - y_i)^2}{N}} \tag{56}$$

Firstly, the impact of the neuron number on the brake pressure estimation performance is analyzed. Considering the complexity of the problem, the estimation performance is tested under different number of neurons ranging from 10 to 100. According to Fig. 7, as the number of neurons changes, the estimation accuracy of the FFNN varies slightly. The best prediction performance is yield by FFNN with the number of neurons at 70.

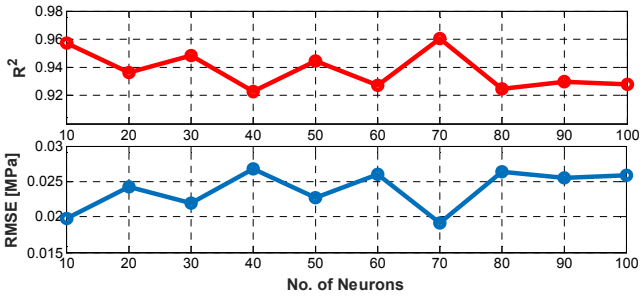


Fig. 7 Estimation performance of FFNN with different number of neurons.

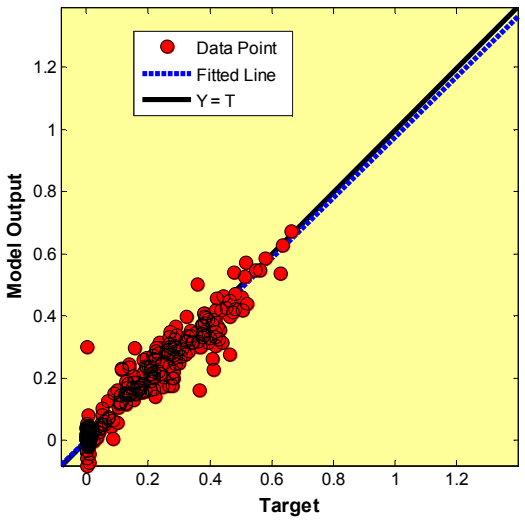


Fig. 8 Regression performance of the FFNN model with 70 neurons.

Then, the linear regression performance of the trained model is investigated. Based on the linear regression result shown in Fig. 8, the test regression result R is of 0.96677, indicating the FFNN model with 70 neurons can accurately estimate the braking pressure through selected features.

Fig. 9 shows the brake pressure estimation result in time domain. The x-axis presents the 1400 samples of the testing data set, and the y-axis shows the estimation results of the scaled brake pressure. Since the input and output data for model training is scaled to the range of [0, 1], the model testing output is then falling within the range between 0 and 1 accordingly. Based on the results, the FFNN model achieves high-precision regression performance, and the RMSE is around 0.1 MPa, demonstrating the feasibility and effectiveness of the developed method.

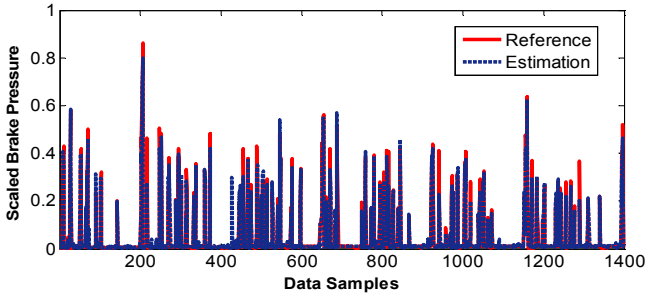


Fig. 9 ANN-based braking pressure estimation results with 1400 testing data points.

B. *Importance Analysis of the Selected Features*

Besides, the utilized feature variables are further investigated through analyzing the importance of predictors [34]. A larger value of the predictor importance indicates that the feature variable has a greater effect on the model output.

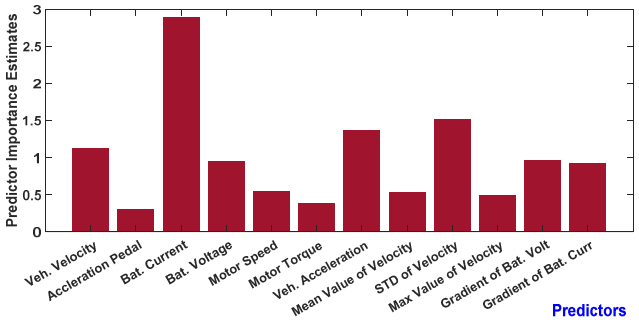


Fig. 10 The predictor importance estimation results.

Fig. 10 illustrates the estimation results of the predictor importance. Based on the results, the most important feature in the model is the battery current, followed by STD of velocity, vehicle velocity, and acceleration. Besides, the battery voltage, the gradients of the battery voltage and current also exert impacts on the model estimation performance.

C. *Comparison of Estimation Results with different Learning Methods*

The developed ANN-based approach is compared with other machine learning methods, including regression decision tree, Quadratic support vector machine (SVM), Gaussian process model, and regression Random Forest. These models are also trained and tested with the 5-fold cross validation method. Apart from R^2 and *RMSE*, other two evaluation parameters, i.e. the training time and the testing time, are also utilized to assess the performance of different models.

Detailed results of the comparison are shown in Table 4. According to the results, the single decision tree algorithm gives much shorter training time and a much faster testing speed in comparison to the other algorithms. In terms of real-time application, the regression decision tree could be a good candidate because of its simplicity and high computation efficiency. However, with respect to the brake pressure estimation accuracy (both R^2 and *RMSE*), the developed ANN algorithm yields the best performance with acceptable training time and testing speed.

TABLE 4
COMPARISON OF BRAKING PRESSURE ESTIMATION PERFORMANCE

Method	R^2	RMSE (MPa)	Training Time (s)	Testing Speed(obs/s)
Decision Tree	0.912	0.133	1.092	~240000
Quadratic SVM	0.867	0.188	141.93	~46000
Gaussian Process model	0.921	0.125	156.89	~8100
Random Forest	0.903	0.104	3.79	~36000
ANN	0.935	0.101	3.42	~82000

VII. CONCLUSIONS

In this paper, a novel probabilistic estimation method of brake pressure is developed for a safety critical automotive CPS based on multilayer ANN with LMBP training algorithm. The high-level architecture of the proposed multilayer ANN for brake pressure estimation is illustrated at first. Then, the standard BP algorithm used for training of FFNN is introduced. Based on the basic concept of BP, a more efficient algorithm of LMBP method is developed for model training. The real vehicle testing is carried out on a chassis dynamometer under NEDC driving cycles. Experimental data of the vehicle and powertrain systems is collected, and feature vectors for FFNN training collection are selected. With the vehicle data obtained, the developed multilayer ANN is trained. The experimental results show that the developed ANN model, which is trained by LMBP, can accurately estimate the brake pressure, and its performance is advantageous over other learning-based methods with respect to estimation accuracy, demonstrating the feasibility and effectiveness of the proposed algorithm.

Further work can be carried out in the following areas: the proposed algorithm will be further refined with onboard road testing; intelligent control algorithms of braking system will be designed based on state estimation.

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Levenberg-Marquardt backpropagation training of multilayer neural networks for state estimation of a safety critical cyber-physical system

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C. Lv, Yang Xing, Junzhi Zhang. Levenberg-Marquardt backpropagation training of multilayer neural networks for state estimation of a safety critical cyber-physical system. IEEE Transactions on Industrial Informatics, Volume 14, Issue 8, August 2018, pp3436-3446

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