Based on Artificial Neural Network to Realize K-Parameter Analysis of Vehicle Air Spring System

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Abstract. In recent years, because of the air-spring control technique is more mature, that air-spring suspension systems already can be used to replace the classical vehicle suspension system. Depend on internal pressure variation of the air-spring, the stiffness and the damping factor can be adjusted. Because of air-spring has highly nonlinear characteristic, therefore it isn’t easy to construct the classical controller to control the air-spring effectively. The paper based on Artificial Neural Network to propose a feasible control strategy. By using offline way for the neural network design and learning to the air-spring in different initial pressures and different loads, offline method through, predict air-spring stiffness parameter to establish a model. Finally, through adjusting air-spring internal pressure to change the K-parameter of the air-spring, realize the well dynamic control performance of air-spring suspension.

1. Introduction

The suspension system is the structure between auto-mobile body and wheel. With more and more widespread use of air-spring, there are many car manufacturers uses for the pneumatic suspension system. Using compressed air inflated or deflated by a spring inside the bellow shape capsule, changes in air pressure inside the spring in order to achieve the adjustment of the spring K parameter and car chassis height adapt to different road conditions.

This research will aim at the different initial pressure and load capacity, is forecast the air suspension soft and hard degree and internal pressure for the kind neural network. Chosen the driving operator schema by the user, the operator schema had decided the suspension system parameters (damping factor and spring constant) (most greatly longitudinal changed and stable time with the system dynamic characteristic highly), but by the change air suspension internal pressure, according to the driver change of demand spring constant, achieved the user to anticipate the pressure scope that by the pressure dependent control opening solenoid valve air admission or the exhaust, realized the goal of spring K value adjustment.

2. Methodology

2.1. Air-spring Introduction and Analysis. In this research, the air spring is a dual winding box with bellow, metal wires are inlaid in the rubber body in order to improve the ability to withstand the pressure of the cavity. Since the air spring K value non-linear characteristics, we can learn that the air spring not only determined by the material of the air spring but also the internal pressure. The coefficient K of the air spring is shown in Eq. (1).
Where, $K_0$ is determined by the air spring material, further initial pressure $p_0$, the amount of stretching of the spring and internal pressure changes will produce different $\Delta K$ increments. Therefore, the air spring $K$ value is nonlinear. In this research, we focus of the relevant parameters of the spring $K$ value variable as the neural network input and output, thereby we can predict the current $K$ value of the air spring and internal pressure [1].

2.2. Particle swarm optimization method combined with neural network learning. A multi-layer feed-forward networks architecture was used in this research[2][3], when the input transformed by the connection weight and activation function, the prediction output of neural network compared with the real target output, by adjusting the weights, so that the prediction output more close to the real output. Its neural training input and output architecture were shown in Fig. 1:

Among them, the neural network training input variable for the initial internal pressure of the air spring and compression spring, a total of two dimensions, as input variable of $Z_1 \sim 2$ in Fig. 1 The output variable

$$K = K_0 + \Delta K$$

(1)
were internal pressure of the air spring and spring coefficients two dimensions, as input variable $y_1, y_2$ in Fig. 1. The neural network connection weight, connecting the input layer to the hidden layer weights number $v_{ij}$ and the connecting hidden layer to the output layer weights number $w_{jk}$, constituting each particle component of the PSO algorithm, the sum of the number of re-ANN rights, such as Eq. (2):

\begin{align}
\text{number of } v_{ij} \text{ weights} : (n + 1) \times m \\
\text{number of } w_{jk} \text{ weights} : (m + 1) \times p \\
\text{number of weights} : (n + 1) \times m + (m + 1) \times p
\end{align}

Among them, $n$ is the input node, $m$ is the number of hidden layer node, $p$ is the output node. Using the Eq. (2) to obtain particle dimension of PSO, by constantly revised weights, selecting weights $v_{ij}$ and $w_{jk}$ to minimize the sum of squared error which represents Eq. (3) below:

$$E_{total} := \frac{1}{2} \sum_{q=1}^{l} \sum_{k=1}^{p} e_{qk}^2, q \in l, k \in p$$

The objective function values calculated by PSO algorithm, change the particle component is minimized so that the objective function[4]. Mean Square Error and Mean Absolute Deviation said that if the Eq. (4) and (5) below, as machine learning to assess the effectiveness indicators.

\begin{align}
\text{MSE} &= \frac{\sum_{q=1}^{l} \sum_{k=1}^{p} e_{qk}^2}{l \cdot p} \\
\text{MAD} &= \frac{\sum_{q=1}^{l} \sum_{k=1}^{p} |e_{qk}|}{l \cdot p}
\end{align}

In the Eq. (4) and (5), $l$ is the total number of data, $p$ is the number of output nodes.

2.3. Controller design. This research will be adjusted the air spring and setting up the rational K value range of the air spring by drivers, according to road conditions in accordance with the driver to air spring parameter K value. Upgrade the intersection the type of input and parameter of neural network, stopping predict the intersection of k value and reasonable range, until predict output the intersection of K and value according with driver. Pressure forecast output pressure becomes the target K value desired internal air spring arrival value. Using pressure dependent control, through the solenoid valve’s on-off, changing the supply of compressed air to the air pressure inside the spring or the spring as part of the internal air emissions, to achieve the appropriate internal pressure, thus achieving the purpose of adjusting spring K value. The controller of this research can be divided into four blocks, it contains offline training the neural network weights, the neural network to predict the output of the operator to adjust the driving pattern and pressure regulation system controller design block diagram, shown as Fig. 2:
3. Resultstructure

3.1. Training the neural network forecasting results. This research experimental stuff is 1,200, is divided into the training material 900 and test material 300, by hideaway level node integer (m) 4–6 forecast that the training material and has not participated in the training flow the test data analyzing. Will conform to the hideaway level node integer and weight value of this research uses the weight value as the forecast. The training and predicting input/output parameter, as shown in Table 1:

| ANN input parameters | Actual output | ANN predicted output parameters |
|----------------------|---------------|---------------------------------|
| Z1                   | Z2            | d1                              | d2 | y1  | y2  |
| Air-spring initial pressure | Spring displacement | Spring internal pressure | Spring K values | Spring internal pressure | Spring K values |

When the kind neural network hideaway level node integer (m) hypothesis is 4–6, obtains the best weight value after the training, the test data by the kind neural network forecast output result, and will compare with the actual output, and may know the forecast output result good or bad degree. Because the hypothesis neural network output integer is 2, in order to demonstrate good or bad degree of its predict...
that will take the abscissa hypothesis as actual output d1 and d2, the ordinate outputs y1 and y2 for the forecast presents the forecast good or bad degree, shown in Fig. 3 to Fig. 5.

![Fig. 3 Test data actual value and predicted value material compare (m=4)](image1)

![Fig. 4 Test data actual value and predicted value material compare (m=5)](image2)

![Fig. 5 Test data actual value and predicted value material compare (m=6)](image3)
In cross-validation method to verify the accuracy of their training and testing [5], and depending on the number of hidden nodes (m= 4–6) interactive validation process of training data and test data of MSE(Mean Square Error, MSE) and MAD(Mean Absolute Deviation, MAD). Results in 10 tests were averaged (Mean) and the number (Median), the number of hidden nodes chosen for this study. The results are shown in Table 2.

Table 2 Different hidden node (m) test data validation results.

| m   | 4   | 5   | 6   |
|-----|-----|-----|-----|
| MSE | Mean | 0.0007 | 0.0004 | 0.0003 |
|     | Median | 0.0007 | 0.0004 | 0.0003 |
| MAD | Mean | 0.0191 | 0.0156 | 0.0135 |
|     | Median | 0.0195 | 0.0162 | 0.0133 |

3.2. Analysis of experimental results. From the results of cross-validation method, the selection (m = 4) hidden nodes as a prediction of the control of the use, the predicted results comply with the requirements of this study and neural network training parameters less than other hidden nodes, so that the training speed increases. For different initial pressures, depicting theoretical, compares actual and forecast Figure shown in Fig. 6. Table 3 is in the different initial pressure, the maximum percentage of predicted and actual neural network regression curve of relative error.
Initial pressure 40 psi

Initial pressure 60 psi
Initial pressure 80 psi

Initial pressure 100 psi
Initial pressure 120 psi

Fig.6 Different initial pressure springs K parameter for theoretical, actual and forecast comparison chart.

Table 3 Different initial pressure, the maximum spring coefficient predicted value and the actual value of the relative percentage error.

| initial pressure (psi) | 20  | 40  | 60  | 80  | 100 | 120 |
|------------------------|-----|-----|-----|-----|-----|-----|
| relative percentage error (%) | 2.1 | 2.5 | 1.2 | 2.9 | 4.1 | 0.7 |

From Fig. 6 and Table 3, at low initial pressure, it predicted a big gap between the actual value, possible reasons for the internal pressure and K values of the two data points with the amount of compression on the more obvious changes, resulting in poor forecasts. Conversely, at high initial pressure, internal pressure and K values vary with the amount of compression is more obvious. Therefore, at high initial pressure, the predicted results are more accurate.

4. Conclusion

The parameters of suspension system decide the main key of riding comfort and handling. For riding on the rough road, the definition of air springs’ shock peak and settling time are operational factors of riding comfort and concussion change time of tire and road. Pneumatic suspension system is subjected to the characteristic of hardware, it cannot and don’t need to react immediately for those small changing road (ex: non slip nosing). The research proposes an effective control policy to the air spring of pneumatic suspension system, according to the driver’s requirement that changes the internal pressure of the air spring make corresponding adjustments, realize good suspension system dynamic control.
The research uses neural network combine with PSO algorithms to learn the characteristic curve of air springs offline, depend on the initial pressure, the maximum percentage error of learning value K and the actual value are less than 5%, therefore it proving the feasibility of neural network predictive value K. With the trained weights, we can predict the spring value K of compression in air spring by different internal pressure. Thus, construct the air spring controller, then predicting the numerical difference between the value K of air spring and driver’s expected value, by pressure-dependent change inside pressure of air spring to reach the perfect spring parameter K..

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References
[1] PresthusM 2002 Derivation of Air Spring Model Parameters for Train Simulation. Lulea University of Technology, M.S. Thesis.
[2] HsiehJG, JengJH and LinYL 2015 Pathways to Machine Learning and Soft Computing.
[3] HaganMT, DemuthHBandBealeM 1996 Neural Network Design, Thomson Publishing Inc.
[4] KennedyJ and EberhartR C 1995 Particle swarm optimization in: Proc. IEEE Int. Conference on Neural Networks, Perth, Australia, Vol. 4 pp1942-48.
[5] KohaviR 1995 A Study of Cross-Validation and Bootstrap for Accuracy Estimation and Model Selection. Appears in the International Joint Conference on Artificial Intelligence (IJCAI), San Francisco, USA, Vol.2, pp1137-43.