Acta Technica 62 (2017), No. 5B, 169–178 © 2017 Institute of Thermomechanics CAS, v.v.i.

Research of deep learning algorithm on intelligent balanced device for beam pumping unit

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Abstract. In order to save energy of the beam pumping unit, the intelligent balanced device is developed. The servo motor of the balanced device is powered by the solar battery and wind power generator which can reduce the power consumption for the pumping unit. In addition, the balanced block can be moved automatically to decrease the torque loading on the reducer's output shaft of the pumping unit. The key point of saving energy for the pumping unit is that the torque loading on the reducer's output shaft is decreased. So the deep learning algorithm is used to control the servo motor. The deep learning network contains convolution neural network (CNN) and fully connected neural network. Firstly, the neural network is training by the dynamometer card image to modify their weight value and bias value. Then, the neural network is applied to the control system. Finally, an application of the intelligent balanced device for the pumping unit is discussed. The maximum torque on the reducer's output shaft is decreased from 14.3KNm to 12.0KNm, and the most important is that the minus torque -20.1KNm is eliminated which can avoid the generating condition for the main motor of the pumping unit. So the results of application shows that the intelligent balanced device can have the good effect of reducing the power consumption.

Key words. Beam pumping units, deep learning, intelligent, saving energy.

1. Introduction

There is a wide application of the beam pumping unit to the oilfield, which is about 90% of the oil production equipment. However, the pumping unit has to consume a large number of electric energy every year. In order to save the energy of the pumping unit, the balanced block is often used to storage and release energy

[1]Acknowledgement - This paper was supported by a grant from the National Natural Science Foundation of China (No.51405385), the Scientific Research Project of Shanxi Province, China (No. 2014K07-20) and demonstrative experimental teaching project of virtual simulation for undergraduate of Shanxi Province, China. The authors want to give their gratitude to them.

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for the pumping unit[1], or the energy saving electric motor is used[2]. In addition, some new types of pumping units were developed, such as Nitrogen over Hydraulic Pumping Unit[3] and long stroke pumping unit[4]. There are three kinds of balanced ways for the beam pumping unit, which are crank balanced way, beam balanced way and compound balanced way. However, these balanced methods have a bad effect when the load on the horse head of the pumping unit changes. The reason is that the position of the balanced block is constant and can not be adjusted automatically. So some new balanced methods have been developed, such as automatic balance regulating device, overrunning clutch device, and the kinetic energy equilibrator.

Muzhou Liu[5] developed the dynamic balanced beam pumping unit, which the position of the beam balanced block can be changed by the traction of a steel rope with the rotation of the horse head. Yanzhao Ren[6] researched a kinetic energy equilibrator of beam pumping units, whose equilibrator is used to save the energy and to avoid the main motor in generating condition. F. Zi-Ming[7] designed a type of secondary balancing pumping unit whose assistant balanced block is installed on the gearbox of the pumping unit to improve the balanced effect. However, the energy saving is limited in the above devices because their balanced blocks can only be moved in a preset movement regulation. Minghao Liu[8] designed an automatic balance regulating device for conventional beam pumping unit. Although the balanced block can be adjusted online, it can not save much energy since the servo motor of the regulating device has to consume the electric power.

Among the new balanced methods, the automatic balanced regulating device has the better effect, which can adjust the position of balanced block in real-time. However, its servo motor may sometimes consume a lot of energy, so it counteracts the energy saving by using the balanced device. Aiming at the problem, the intelligent balanced device is designed in this paper, whose servo motor can be powered by the solar batteries and wind power generators. So it can realize the actual energy saving for the pumping unit.

The balanced effect of the pumping unit can be evaluated by the torque loading on the reducer's output shaft[9][10]. If the torque is positive and small, the main motor of the pumping unit consumes a little power. The torque loading on the reducer's output shaft is determined by the horse head load, the weight and position of the balanced blocks. So it is very important to control the movement of the balanced blocks. However, the conventional control method can not achieve the good effect. In recent years, the deep learning algorithm has been a hot topic in many research field[11][12]. It can realize the self-learning to adapt the change the environment. So the intelligent control method based on the deep learning algorithm is designed in this paper.

The paper is organized as follows: Firstly, the background of the intelligent balanced device for the pumping unit is introduced in section 1. Next, the whole structure of the intelligent balanced device for the pumping unit and the control method based on the deep learning are discussed in section 2. Then, The deep learning algorithm are analyzed in section 3. Next, the application of the device is presented in section 4. Finally, the conclusions are arrived at in section 5.

2. THE STRUCTURE OF THE INTELLIGENT BALANCED DEVICE OF THE PUMPING UNIT

2.1. Principle of the Intelligent Balanced Device

The whole structure of the intelligent balanced device of the pumping unit is shown in Fig.1. The horse head of the pumping unit can be rotated reciprocated driven by the main motor of the pumping unit. So the suspended point is moved vertically reciprocated. Since the load of the rod string is very large and variable, which is often from 30KN to 100KN, the balanced blocks can be used to decrease the driving torque of the main motor of the pumping unit. Here the two balanced blocks can be installed in the pumping unit, i.e. the beam balanced block and the crank balanced block, as is shown in Fig.1. The crank balanced block is fixed on the crank of the pumping unit and it can not be moved. Whereas, the beam balanced block can be moved axially along the intelligent balanced device. The beam balanced block is installed on the lead screw of the intelligent balanced device, and the lead screw is linked by the servo motor. When the servo motor is turned on, the lead screw rotates about its axis driven by the servo motor. So the beam balanced block can be moved along the lead screw. Since the intelligent balanced device is located on the beam of the pumping unit, the movement of the block can change the balance effect for the pumping unit. When the load of the rod string on the horse head is bigger, the balanced block can be moved toward left in order to increase the length of the arm of force. But when the load of the rod is smaller, the balanced block can be moved toward right.

For the conventional balanced device, although the beam balanced block can decrease the electric power consumption of the main motor of the pumping unit, the servo motor has to consume the electric power. The power consumption of the servo motor is sometimes equal to the power saving of the main motor. So it can not save the energy actually.

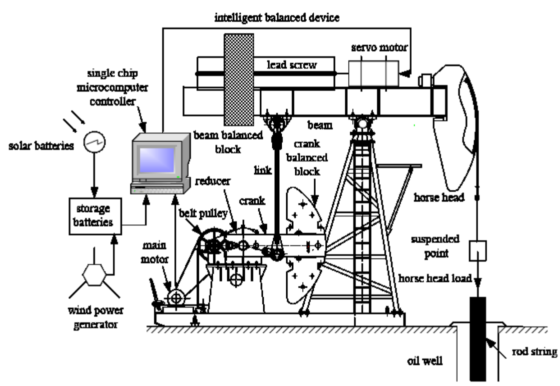

Fig. 1. Whole Structure of the Intelligent Balanced Device

So, the intelligent balanced device is designed in this paper. The key point of the intelligent balanced device is the method of power supply for the servo motor. Here the servo motor is powered by the solar batteries and the wind power generator. Then, the servo motor need not consume the power which supply for the pumping unit. Hence it can realize the energy saving actually compared with the conventional method.

In fig.1, the servo motor is controlled by the single chip microcomputer controller. The current signal and voltage signal are inputted into the single chip microcomputer controller. In addition, the solar batteries and the wind power generator are also connected to the single chip microcomputer controller through storage batteries.

2.2. The control method of deep learning

The key point of the intelligent balanced device is to control the movement of the beam balanced block. Because the beam balanced block is driven by the servo motor, the servo motor should be controlled properly. However, there exists the nonlinear and other non-predicted factors, the conventional control methods can not achieve a good effect. So, the control method based on deep learning is designed in this paper. The structure of the control algorithm is shown in Fig.2. Firstly, the dynamometer card image is inputted to the convolution network(CNN) C1. Then the output of C1 is inputted into pooling S2 in order to decrease the dimensions of the image and increase the efficiency of calculation. The convolution layers include C1, C3 and C5. The pooling layers include S2, S4 and S6. The output of S6 is applied to the F7. The neural network F7, F8 and F9 are fully connected, which they contain 12 nodes separately. F10 is also a fully connected network, but it has only one node. Finally, the output of F9 is added to get the us. Then us is inputted into the servo driver, which the servo driver control the servo motor.

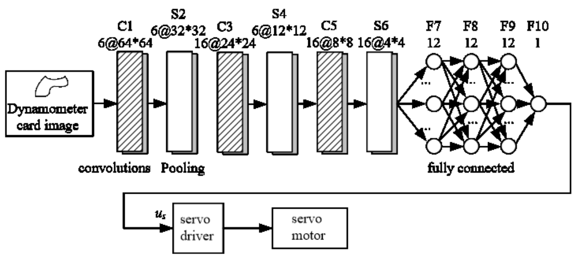

Fig. 2. structure of the control system based on deep learning

3. The deep learning algorithm

3.1. The signal process of neural network

From Fig.2, it can be seen that the dynamometer card image is 128*128 and the CNN C1 has the dimension of 64*64 and the depth of 6.

$$C_i^j = conv2(A, K_i^j, valid) + b_i^j \tag{1}$$

$$m_i^j = C_i^j \tag{2}$$

$$a_i^j = f(m_i^j) \tag{3}$$

where, C_i^j is convolution result of current layer C_i^1, C_i^3 and C_i^5(j=1,3,5). ai is the inputted feature map. $K_i^j$is the convolution kernel. For the layer C1, C3 and C5, K_i^1, K_i^3 and K_i^5 are 65*65, 9*9 and 7*7 respectively; valid means the narrow convolution method; m_i^j is a middle variable; ai is the output of current layer C1, C3 and C5(i=1,3,5); $b_i^j$is the bias value. f() is the activation function, which the Sigmoid function is used. For the fully connected layers, it is:

$$f(x) = \frac{1}{1+\exp^x} \tag{4}$$

For the C1, C3 and C5, the activation function is:

$$f(x) = \begin{cases} x & x > 0 \\ 0 & x \le 0 \end{cases} \tag{5}$$

The input feature map of pooling layer S2 is 64*64 and the depth S2 is 6. The window of the S2 is 2*2. So the input feature map from C1 will be converted into 32*32. The input feature map of pooling layer S4 is 24*24 and the depth of pooling layer is 6. The window of the S4 is 2*2. So the input feature map from C3 will be converted into 12*12. Similarly, The input feature map of pooling layer S6 is 8*8 and the depth of pooling layer is 6. The window of the S4 is 2*2. So the input feature map from C3 will be converted into 4*4.For the pooling layers S2, S4 and S6:

$$S_i^j = down(a_i^{j-1}) + b_i^j \tag{6}$$

$$m_i^j = C_i^j \tag{7}$$

$$a_i^j = f(m_i^j) \tag{8}$$

Where, j=2,4,6. 'down' means the signal is forward propogation. a_i^{j-1} is the inputted into the current pooling layer from the above convolution layer. $b_i^j$is the bias value. m_i^j is a middle variable. f() is also the Sigmoid activation function.

The fully connected layer F7, F8 and F9 have 12 nodes respectively. their output can be written as:

$$z_i^j = w \times a_i^{j-1} + b_i^j \tag{9}$$

$$m_i^j = z_i^j \tag{10}$$

$$a_i^j = f(m_i^j) \tag{11}$$

Where, j=7,8,9. $z_i^j$is the input of the current layer and a_i^j is the output of the current layer. w is the weight value of the current layer. b_i^j is the bias value of the current layer.

3.2. Training of the

Training for the CNN and the fully connected layers are with supervised learning and they need the sample collection. The procedure of the trainning includes the forward propogation and backward propogation. The main purpose of forward propogation is to calculate the output of each layer according to Eq.(1)- Eq.(10). During the backward propogation, the weight value can be modified accroding to output error. The training procedure is as:

1) To find a proper sample collection and select some data randomly. For this system, the input data is dynamometer card image and the output data is control voltage Uc applied on the servo motor;

2) To initialize the parameters, such as the weight value of net work, the bias value, output accuracy and learning rate;

3) To input a group of sample data into the C1 layer. Then to calculate the output of each layer and us, as in Fig.2;

4) To compare the output of fully connected layer with the predicted output of sample data. So the error can be calculated. Then the weight value of net work, the bias value can be modified according to the error. The modified equation are as follows:

$$J(w,b) = \frac{1}{m}\sum_{i=1}^{m} J(w,b;x^{(i)},y^{(i)}) \tag{12}$$

$$J(w,b;x^{(i)},y^{(i)}) = \frac{1}{2}(y^{(i)} - h_{w,b}(x^{(i)}))^2 \tag{13}$$

Eq.(12)-(13)are the loss function, which can determine the optimal weight value and bias value. Where, x(i) is the input data of layer C1 and y(i) is the output of the fully connected layer F10. h(x) is the calculated output of each layer. According to Eq. (12)-(13), the weight value and the bias value can be modified. The modified equation of fully connected layers is:

$$\delta^{(5)} = \frac{\partial J}{\partial z^5} = \frac{\partial}{\partial z}(y - h(x))^2 = \frac{\partial}{\partial z^5}(y - f(z^5))f^{'}(z^5) \tag{14}$$

For the CNN layers of C1, C3 and C5, the modified equation of weight value and bias value is:

$$w^{(l)} = w^{(l)} - \alpha\frac{\partial J}{\partial w^{(l)}} \tag{15}$$

$$b^{(l)} = b^{(l)} - \alpha\frac{\partial J}{\partial b^{(l)}} \tag{16}$$

The calculation equation is:

$$up(\begin{vmatrix} 1 & 2 \\ 3 & 4 \end{vmatrix}) = \begin{vmatrix} 1 & 1 & 2 & 2 \\ 1 & 1 & 2 & 2 \\ 3 & 3 & 4 & 4 \\ 3 & 3 & 4 & 4 \end{vmatrix} \tag{17}$$

5) The neural network is trained by all the sample data;

6) After the iteration is made in many times, the error between the output of neural network and the predicted output is checked. If the error is lager than the permitted accuracy, we should return step 3). And if the error is smaller than the permitted accuracy, we can continue the next step;

7) After the neural network is trained, it can be used to control the servo motor in Fig. 1.

4. APPLICATION

4.1. Training for the deep learning network

The deep learning network is trained by the sample data. The sample data is dynamometer, which is sampled from YanChang oil field in China. The dynamometer card image is shown in Fig.3. The simulation is made in Windows operating system. The deep learning algorithm program is run in MATLAB. The structure of neural network is shown in Fig.2. The dynamometer card image is 256*256.

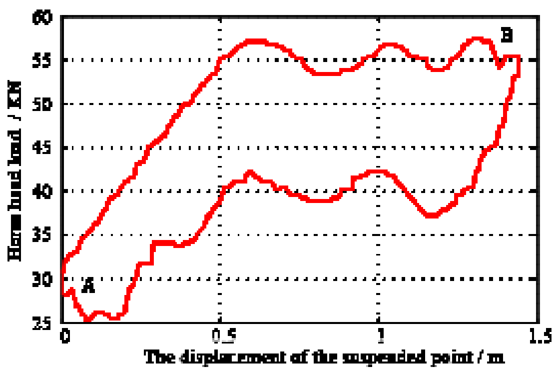

Fig. 3. the training sample data of dynamometer card image

4.2. Results

When the deep learning network is used to control the servo motor, the servo motor can drive the beam balanced block. The control effect can be seen through the torque applied on the reducer's output shaft. The results are shown in Fig.4. In Fig.4., the green solid-circle curve line indicates the torque on the reducer's output shaft generated by the horse load, which the maximum value of the torque is 47.8KNm and the minimum value is -37.6KNm. Since the torque is very big, the blocks should be used. The blue solid curve line shows the torque on the reducer's output shaft when the blocks are used. The maximum value is 14.3KNm and the minimum value is -20.1KNm. In this case, the torque is still minus because the position of the balanced blocks is not adjusted optimal. The beam balanced block are adjusted automatically according to the deep learning algorithm and the torque is indicated by red solid curve line in fig.4. From the red curve line, it can be seen that torque is positive when θ is 0-20°, 180-231° and 281-305°. So it has the best effect contrary to the other curve lines, which can verify the control effect of the deep learning algorithm for the intelligent balanced device in this paper.

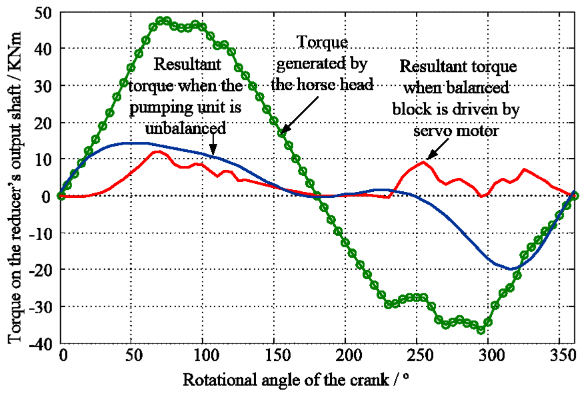

Fig. 4. Torque on the Reducer's Output Shaft

5. CONCLUSIONS

In order to realize the energy saving for the pumping unit, the intelligent balanced adjustment device of the pumping unit is designed. Compared with the other device available, this device is powered by the solar batteries and wind power generator. Since the servo motor did not consume the power supplied for the pumping unit, it realizes the actual energy saving.

Since the conventional pumping unit has a fixed position of the balanced block, its balance effect is not often the optimum. The torque on the reducer's output shaft is sometimes very big, even minus, which causes the main motor of the pumping unit to waste energy. However, the balanced block can be moved automatically in the intelligent balanced adjustment device for the pumping unit. And the movement of the balanced block is controlled by using the deep learning algorithm. So it can improve the balance effect of the pumping units. From the application in section 4, it can be seen that the maximum torque on the reducer's output shaft is decreased and the minus torque is eliminated. So it verifies the effect of the device in this paper.

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Received November 16, 2017