RESEARCHES ON FUNCTION-LINK ARTIFICIAL NEURAL NETWORK BASED LOAD CELL COMPENSATION

Zhu Zijian

Mettler-Toledo (Changzhou) Precision Instrument Ltd.
Changzhou, Jiangsu, China

ABSTRACT

A new approach to load cell compensation modeling based on a function link neural network is discussed in this paper. It firstly introduces the function-link neural network to compensate both linearity and temperature effect of a load cell. An example is given to illustrate the proposed method. Various of coefficients of this network is discussed including the different compensation results on three functional expansion, the relationship between initial learning step and compensation accuracy and etc. A proper network is worked out to compensate load cell up to OIML C10 degree in this paper. This neural network compensation of the above errors was achieved via micro controller. Results in this paper indicate that with above compensation the accuracy of a transducer could be improved greatly. This approach for sensor modeling is superior to the existing techniques. It has a potential future in the field of measurement.

1. INTRODUCTION

Generally, there are two approaches for temperature and linearity compensation ---analog compensation and digital compensation. Analog linearity compensation typically carry out with the semiconductor connected paralleling in the Wheatstone bridge or employ nickel gage for both sensitivity temperature and linearity compensation. The analog temperature compensation includes zero and sensitivity temperature compensation. The principle for these compensation is quite simple----sensitivity temperature compensation use nickel gage with greater temperature coefficient series in the excitation part of the bridge while zero temperature compensation use copper wire series in the bridge to correct error. Due to many factors (material, manufacture…) these methods can not achieve high accurate result.

Digital linearity compensation means all the compensation is through digital data processing method after the load cell signal transfer from analog to digital. Following is three typical methods: Math model method¡ê?Lookup table method¡ê? Interpolation method: The combination of the above two method. Method for digital compensation of temperature adopt two quadratic equation that separately correct zero and sensitivity temperature errors. An integrated model for both linearity and temperature compensation is another approach. It firstly works out a series of constants for the fitness of linearity with the test data under different temperature, then use these temperature related constants as independent variable to work out the final formula.

This paper presents another digital compensation method by adopting different math modeling. It is based on function link artificial neural network and presents more accurate and flexible comparing with the traditional math modeling. Once upon the network parameters trained have been decided, the model for this kind of cell is established. Meanwhile, the weights of the network are different from cell to cell for this kind of load cell.

2. FUNCTION LINK ARTIFICIAL NEURAL NETWORK (FLANN)

Function link artificial neural network is basically a flat single layer network in which the need of hidden layer has been removed by incorporating functional expansion of the input pattern.

The functional expansion effectively increases the dimensionality of the input vector, and hence the hyperplanes generated by the FLANN provide greater discrimination capability in the input pattern space. Both non-hidden layer and enhanced input pattern space make this network high precision of function approximation. It has been proposed for exacted calculation. In general, BP network is the most popular artificial neural network, but due to the BP (back propagation) network slow convergence, easy to fall in local least point of energy, it is typically employed in pattern recognition system. So, here we chose function link neural network to establish the linearity and temperature compensation math model.

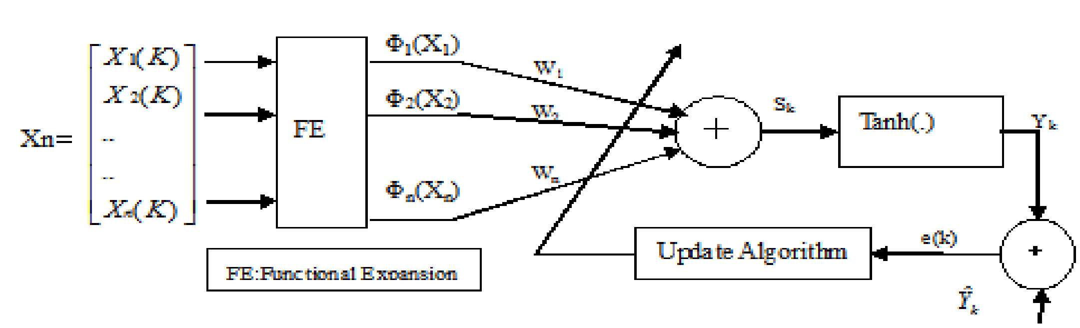


Figure1: General structure of FLANN

Enhancing the input layer has three approaches: functional expansion, combined convolution, and the combination of both. Here we employ the functional expansions. There are three different polynomials for functional expansion of the input pattern in the FLANN. They are Chebyschev, Legendre and power series. In a certain FLANN system, it is important to choose suitable functional expansion of the input pattern using an appropriate polynomial function. Principally the simple expansion will be adopted if the accuracy is enough for requirements. The following sections will discuss the scheme for the two functional expansion mentioned above.

3. THE SCHEME OF LINEARITY AND TEMPERATURE COMPENSATION MODELING

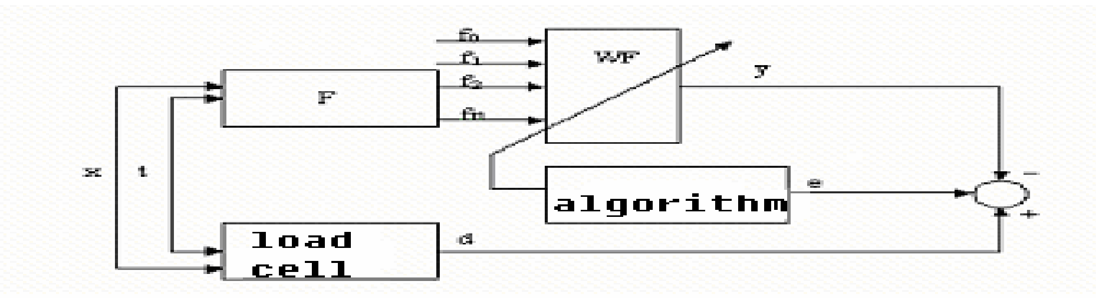


Figure2: The layout of the system

In this load cell modeling, the inputs to the FLANN consist of normalized temperature *t*, and normalized weight value *x*, and the desired (or the target) output for the network *d* is the normalized applied weight. *y* is the estimated value which is the output of the network. F is the functional expansion part, it could be additional function and the cross-product term for *x* or *t*. By analyzing the performance for different type of load cell, choosing proper functional expansion, training the network with load cell test data generated at different temperature until the mean square error between the desired and FLANN output reaches a preset minimum value, and become convergence. Respectively, the iteration, the learning algorithm, the learning parameter, the momentum factor, the initial learning step and the rate of learning step and other network coefficients are all the factor that influence the accuracy and convergence of the network.Of course, to guaranteed all these compensation working well is the load cell has good repeatability. In the real application, if the accuracy can not meet the requirement, we should add some new training data to update the model.

The FLANN-based scheme works in two modes: training-mode and test-mode. During training-mode, the data patterns from the training-set are applied to the FLANN and subsequently its output is computed. Next, the weights of the FLANN are updated using the BP learning algorithm. The training procedure continues considering all patterns of the training-set till the error reduces to a pre-set minimum value. Next, the weights of the FLANN are frozen and stored in an EEPROM for testing of the model to verify its performance, and for actual use. During test-mode, these stored weights are loaded into the FLANN. Then, the input patterns from the test-set are applied, and the model output is computed. If the model output matches closely with the actual applied weight, then it may be said that the FLANN has learned the load cell characteristics correctly.

Implement step:
Assuming *x* is the weight signal, *t* is the temperature signal, and *F* is the functional expansion. After pass through the *F* block, the output produces *f1¡ê?…,fn*¡ê?then

$$Y_i = W^T F_i = F_i^T W \qquad (1)$$

where W=$[w_0,w_1, \ldots,w_n]^T$¡ê? $F_i=[f_1$¡ê?$f_2,\ldots,f_n]^T$?¡ê
let desired output is *di*¡ê?then,

$$E(k) = \frac{1}{2}\left[\sum_{i=1}^{I}(d_i - y_i)^2\right] \qquad (2)$$

E(k) is the error at kth instant¡ê?the output will come out the proper weights *W* when the error is acceptable. If the E (k) is greater than the preset value, then the *W* could be adjusted as follow:

$$W(k) = W(k-1) + \Delta W(k) \qquad (3)$$

$$\Delta W = -\eta(k)\nabla(\varepsilon_i) = \eta(k)(d_i - F_i^T W)F_i \qquad (4)$$

$$\eta(k+1) = \eta(k) - \frac{\beta(E(k) - E(k-1))}{E(k)} \qquad (5)$$

Where *ß* is a constant and 0<ß<1. After iteration calculation, a simple *F* will be worked out after throw out those functions with absolute minimum weights during the calculation.

Preparation of the data-set:
The test data of an uncompensated load cell with which accuracy is 1.3% F.S is as follow:

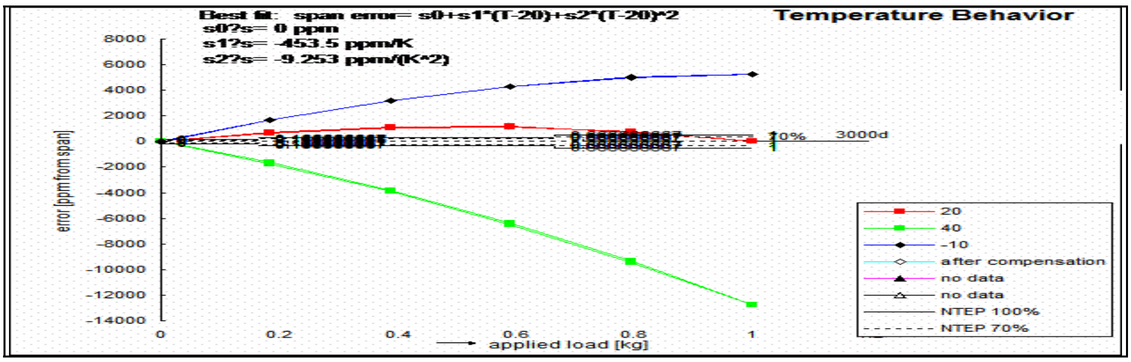


Figure3: Load cell uncompensated performance

Study on different functional expansions:

Case 1: The functional expansion is as follow (power series):

$$f_1 = x, \quad f_2 = x^2 \quad f_3 = t \quad f_4 = t^2 \quad f_5 = xt \quad f_6 = x^3, \quad f_7 = t^3, \quad f_8 = x^2 t, \quad f_9 = xt^2$$

$$F = [1, f1, f2, f3, f4, f5, f6, f7, f8, f9]$$

$$W' = [w1, w2,, w3, w4, w5, w6, w7, w8, w9, w10]$$

$$Y = \sum_{i=1}^{9} F_i \bullet W_i \qquad (6)$$

The compensated test data for load cell employing with this model is as follow:

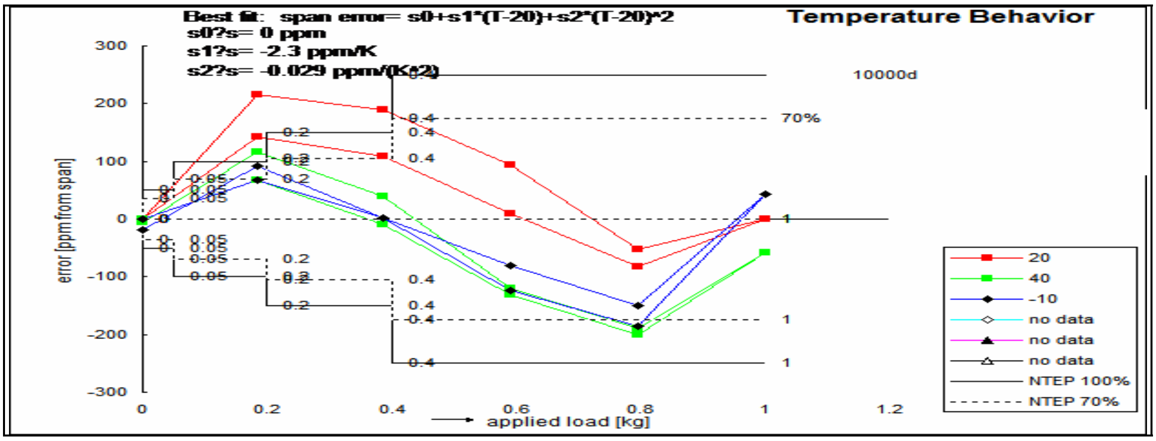


Figure4: Result for case 1

Case 2: In case 2, the network coefficient is the same as case 1, the only different is the functional expansion, and it is:

$$f_1 = x, \quad f_2 = x^2 \quad f_3 = t \quad f_4 = t^2 \quad f_5 = xt \quad f_6 = x^{\frac{1}{2}}, \quad f_7 = t^{\frac{1}{2}}, \quad f_8 = x^{\frac{1}{2}} t^{\frac{1}{2}}, \quad f_9 = xt^{\frac{1}{2}}$$

The compensated test data for load cell employing with this model is as follow:

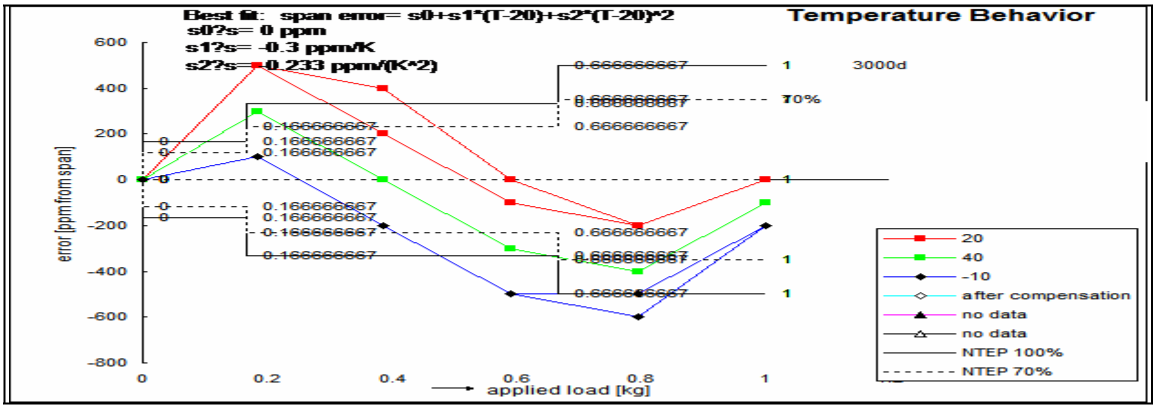


Figure5: Result for case 2

Case 3: The same network coefficient as case 1 and case 2 but the functional expansion is chebyschev polynomials (-1<x<1).

$$f_1 = 1, f_2 = t, f_3 = 2t^2 - 1, f_4 = 4t^3 - 3t, f_5 = x, f_6 = 2x^2 - 1$$

$$f_7 = 4x^3 - 3x, \quad f_8 = xt, \quad f_9 = (2t^2 - 1)x, \quad f_{10} = (2x^2 - 1)t$$

The compensated test data for load cell employing with this model is as follow:

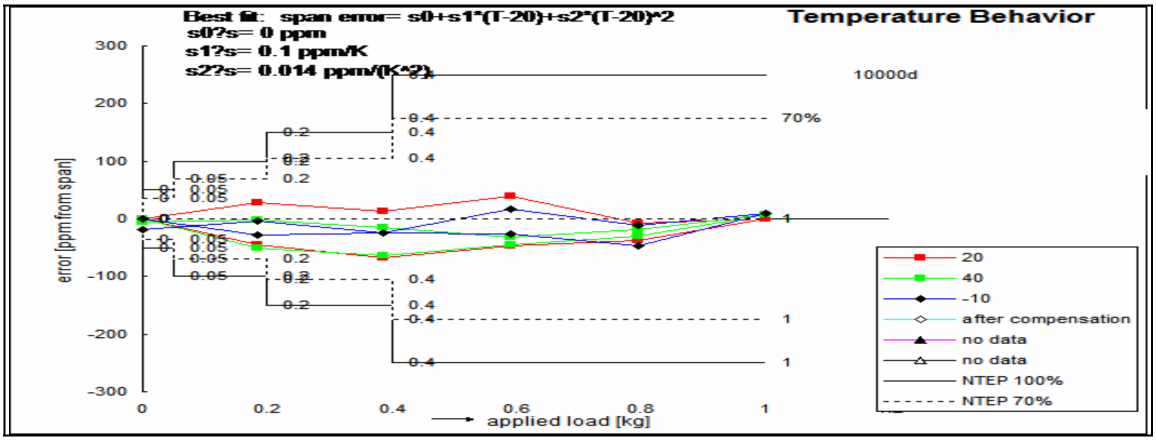
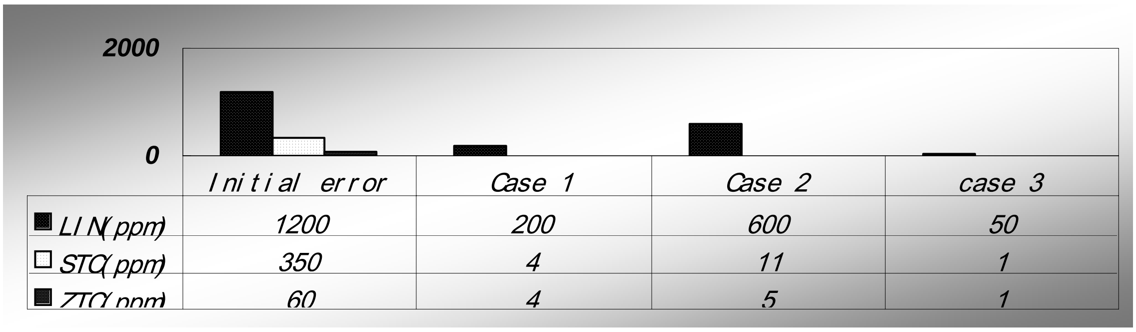


Figure6: Result for case 3



	Initial error	Case 1	Case 2	case 3
LIN(ppm)	1200	200	600	50
STC(ppm)	350	4	11	1
ZTC(ppm)	60	4	5	1

Figure7: The comparison of these three cases

Conclusion: Figure 4,5,6,7 shows that case 2 is not capable for accurate estimation, case 1 is quite good (up to OIML C6) and case 3 with which the chebyschev polynomials is employed, the expansion is simple with high accuracy. It is the best model for this load cell characteristic estimation and is able to reach the requirement for OIML C10.

Effect for initial learning step: Here we use the case 3 functional expansion, iteration=20000:

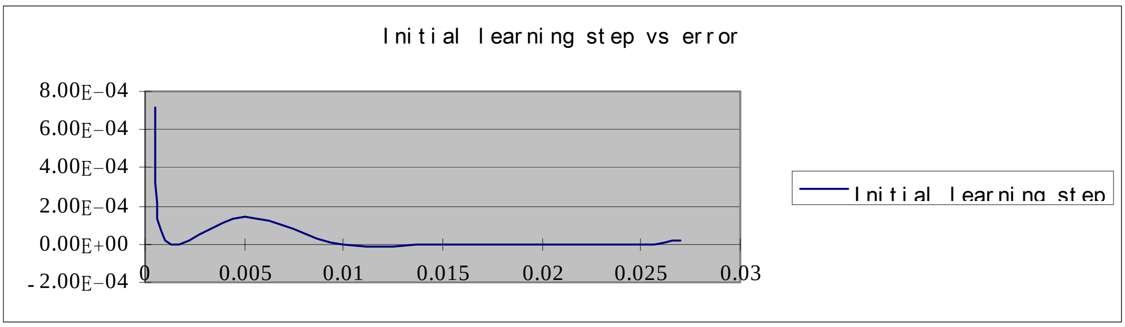


Figure8: The effect of initial learning step

Conclusion: if the initial learning step is too big then the network will become divergence. Once the initial learning step is smaller than a certain value, the network becomes convergence. Here, if it is smaller than 0.005, then the accuracy drop down. So the value should be between 0.25 to 0.01.

Effect for the rate of learning step: The same network as above:

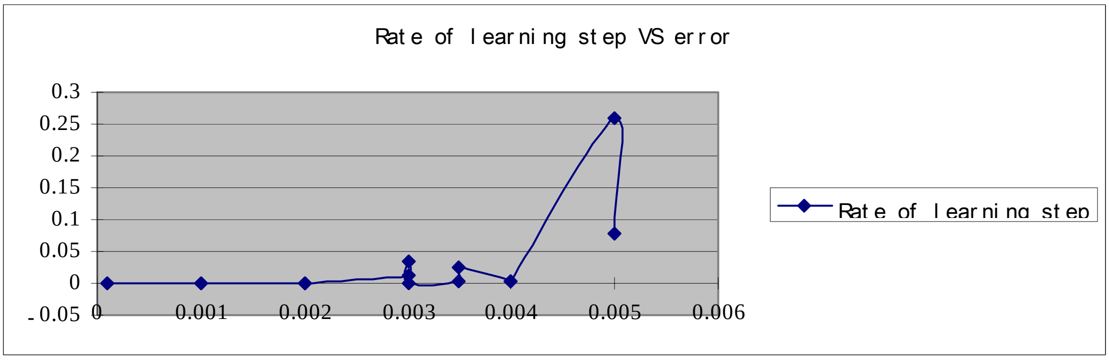


Figure9: The effect of the rate of learning step

Conclusion: If the rate of learning step is too big, the network will become divergence. If it is around critical point,the network becomes unstable. Here, if ß is smaller than 0.001, the network is able to become convergence. Respectively, the smaller it chooses the longer it takes. In the example of this paper, the training time can reach within 2-3 minutes.

4. CONCLUSION

A function link neural network was employed according to the characteristic of the nonlinear error and temperature error. The neural network compensation of the above errors was achieved via micro controller. Results in this paper indicate that with above compensation the accuracy of a transducer could be improved greatly. Because of the simplicity, reliability and flexibility of the above compensation algorithm, it is suitable for high accurate compensation of a load cells.

REFERENCES

[1] Patra J C. An artificial neural network based smart capacitive pressure sensor. Measurement,1997, 113-121

[2] S. Haykin. Neural Networks. Maxwell Macmillan. Ontario, Canada, 1994

[3] Y.H.Pao, Adaptive Pattern Recognition and Neural Network. Reading, MA: Addision-Wesley, 1989.

[4] Pao, Yoh-Han; Phillips, Stephen M. Function link net and learning optimal control , Neural computing, v 9, n 2, Oct, 1995, pp 149-164

[5] Pao, Yoh-Han; Takefuji, Yoshiyasu ,Functional-link net computing: theory, system architecture, and functionalities , Computer, v 25, n 5, May, 1992, pp 76-79C

[6] Patra, Jagdish C. Bos, Adriaan ,Modeling of an intelligent pressure sensor using function_linkartificial neural networks , ISA Transactions, v 39, n 1, 2000, pp 15-27

Addresses of the Authors:

Zhu_zijian , Mettler-Toledo (Changzhou) Precision Instrument Ltd.
Hua shan Road, Sanjing Industry Park, Xinbei District , Changzhou ,Jiangsu, China.
Postal code: 213022

zijian.zhu@mt.com