Prediction Simulation for the Length of Garment Marking Based on QPSO-DFNN

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Abstract: Because of the defects of a posteriori and experience-depended traditional method, a prediction model of the length of garment marking based on dynamic fuzzy neural network (DFNN) combined with Quantum-behaved Particle Swarm Optimization (QPSO) was proposed. The salient characteristics of the method are: 1) hierarchical on-line self-organizing learning is used; 2) neurons can be recruited or deleted dynamically according to their significance to the system's performance; and 3) fast learning speed can be achieved. Data obtained from 32 and 10 groups are used for the dynamic fuzzy neural network learning and simulation respectively. The simulation results demonstrate that DFNN can be used as a prediction system for the length of garment marking and absolute value of the maximum relative error less than 5.11%, and mean absolute percentage error less than 2.01%. The DFNN may be the construction for factory to estimate the fabric consumption and provide a new method for designing optimal cutting plan.

1. INTRODUCTION

Over the years, the length of garment marking can be estimated through CAD layout simulation and experience estimation method [1-4]. The layout simulation method transfers the samples to the system repeatedly for automatic layout according to different ways of layout. Then, fabric costs can be calculated according to the marking length reported by software real-time performance. The samples used in the process of layout need to be prepared in advance, which is time-consuming and tedious. Not to mention, sometimes, we only know about the type, color and quantity of the garments in order roughly in advance. Experience estimation method is based on the actual experience of the master. Given the width of the fabric, it estimates that how long we clip for a few patterns of a certain style in the same layout under the particular scheme. Although the method is simple and direct, it is not easy to promote because of its over-reliance on the master's work experience. The literature [5] gives a linear model about marking length, garment specification and circumference by experimental regression, whose result is between the simulation layout method and experience estimation. It not only eliminates a series of tedious processes of pattern making, but also improves the accuracy, reducing the experience-dependence. Once the regression equations are determined, each parameter weight will not be self-organizing, self-learning which results in weakening the flexibility and practicality with the addition of new samples. Regarding the defects of a posterior and

experience-depended traditional method, the literature [6] proposes to use BP neural network to predict the length of garment marking and the prediction accuracy is superior to the multiple regression method. There exist some significant advantages of the neural network such as the ability of self-learning and self-adaptability, good robustness and generalization performance, so that it can handle with complex, non-linear problem in a better way. However, this method has some flaws. For example, its structure is complex and difficult to choose. In addition, it may trap into local minimum, where it has not clear physical meaning. Fuzzy neural network is the product of the combination of fuzzy system and artificial neural network technology, it attempts to retain the advantage of both and overcome their inherent shortcomings. In recent years, as a hot issue concerned by artificial intelligence scholars, now it has been widely applied in the engineering domain. In this paper, a prediction model of the length of garment marking based on dynamic fuzzy neural network (DFNN) combined with Quantum-behaved Particle Swarm Optimization(QPSO) was proposed. This method realizes online learning and automatically extraction of fuzzy rules with the features of small structure and high learning speed, avoiding over-fitting and is well suited for real-time control and modeling. Simulation experiments show that this method has better precision than BP neural network and provides a scientific and effective prediction technique for the length of garment marking.

2. DYNAMIC FUZZY NEURAL NETWORKS

2.1. Structure and Self-Learning Algorithms of DFNN

The new structure based on extended RBF neural networks to perform TSK model-based fuzzy system is

shown in Fig. (**1**). Comparing with standard RBF neural networks, the term "extended RBF neural networks" implies that: 1) there are more than three layers; 2) no bias is considered; and 3) the weights may be a function instead of a real constant [7].

Layer 1: Each node represents an input linguistic variable in this layer.

Layer 2: Each node represents a membership function (MF) which is in the form of Gaussian functions:

$$\mu_{ij}(x_i) = \exp[-\frac{(x_i - c_{ij})^2}{\sigma_j^2}], \quad i = 1,2,\cdots,r, \quad j = 1,2,\cdots,u \qquad (1)$$

where μ_{ij} is the jth membership function of x_i, c_{ij} is the center of the jth Gaussian membership function of x_i, σ_j is the width of the jth Gaussian membership function of x_i, r is the number of input variables and u is the number of membership functions.

Layer 3: Each node represents a possible IF-part for fuzzy rules. For the jth rule R_j, its output is

$$\varphi_j = \exp\left[-\sum_{i=1}^{r}(x_i - c_{ij})^2 / \sigma_j^2\right] = \exp\left[-\left\|X - C_j\right\|^2 / \sigma_j^2\right], \qquad (2)$$
$$j = 1,2,\cdots,u$$

where $X = (x_1, x_2, \cdots, x_r) \in \Re^r$ and $C_j = (c_{1j}, c_{2j}, \cdots, c_{rj}) \in \Re^r$ is the center of the jth RBF unit. From (2) we can see that each node in this layer also represents an RBF unit.

Layer 4: We refer to these nodes as N (normalized) nodes. Obviously, the number of N nodes is equal to that of R nodes. The output of the N_j node is

$$\psi_j = \varphi_j / \sum_{k=1}^{u} \varphi_k, \qquad j = 1,2,\cdots,u \qquad (3)$$

Layer 5: Each node in this layer represents an output variable as the summation of incoming signals

$$y(X) = \frac{\sum_{i=1}^{u}\left[\omega_i \exp\left(-\frac{\|X - C_i\|^2}{\sigma_i^2}\right)\right]}{\sum_{i=1}^{u}\exp\left(-\frac{\|X - C_i\|^2}{\sigma_i^2}\right)} \qquad (4)$$

where y is the value of an output variable and ω_k is the weight of each rule. For the TSK model

$$\omega_k = a_{k0} + a_{k1}x_1 + \cdots + a_{kr}x_r, k = 1,2,\cdots,u \qquad (5)$$

The learning algorithm of the DFNN comprises 4 parts: (1) criteria of rules generation; (2) allocation of premise parameters; (3) determination of consequent parameters and (4) pruning technology. For the ith observation (X_i, t_i), where t_i is the desired output, calculate the distance $d_i(j)$ between the observation X_i and the center C_j of the existing RBF units, i.e.,

$$d_i(j) = \left\|X_i - C_j\right\|, \quad j = 1,2,\cdots,u \qquad (6)$$

where u is the number of existing RBF units.

Find

$$d_{min} = \arg \min(d_i(j)) \qquad (7)$$

If

$$d_{min} > k_d \qquad (8)$$

an RBF unit should be considered.

On the other hand, define

$$\left\|e_i\right\| = \left\|t_i - y_i\right\| \qquad (9)$$

If

$$\left\|e_i\right\| > k_e \qquad (10)$$

an RBF unit should be considered. Here, k_e, k_d were chosen as

$$k_e = \max[e_{max} \times \beta^i, e_{min}], \quad k_d = \max[d_{max} \times \gamma^i, d_{min}] \qquad (11)$$

where e_{max} is the predefined maximum error, e_{min} is the desired accuracy of DFNN, β is the convergence constant, d_{max} is the largest length of input space, d_{min} is the smallest length of interest, and γ is the decay constant.

Besides, there are other four parameters to be tuned for setting an DFNN, namely, k, k_ω, k_{err} and σ_0. The flowchart of the learning algorithm for the DFNN is depicted in Fig. (2). Readers are referred to Er *et al.* [8] for details. The DFNN performance is strongly dependent on these parameters. Specially, the preliminary experimental results demonstrate that the performance of DFNN are more sensitive for β, γ and σ_0, compared with other parameters. Thus quantum-behaved particle swarm optimization algorithm (QPSO) is used to determine the three parameters of dynamic fuzzy neural networks in this paper.
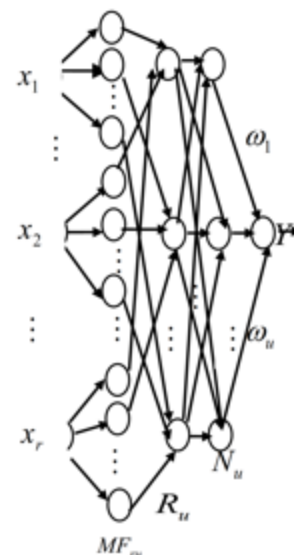

Fig. (1). Structure of dynamic fuzzy neural network.

2.2. Quantum-behaved Particle Swarm Optimization

QPSO is a new PSO algorithm by studying the convergence behavior of particles from quanta mechanical angle [9-12]. This algorithm treats each individual as a volume-less and weight-less particle, and flies at the certain speed in the n-dimensional search space. Each particle represents one position in the n-dimensional space, adjusting its position in the following two directions: (1) the best position of each particle ever discovered; (2) the best position of particle swarm.

Each particle provides the following information: (1) the position vector of particle $x_i = [x_{i1}, x_{i2}, \cdots, x_{id}]$; (2) the best previous position, giving the best objective function value, of particle i called personal best position $P_i = [P_{i1}, P_{i2}, \cdots P_{id}]$ (*pbest*); (3) the position of the best particle among all the particles in the population called global best position $P_g = [P_{g1}, P_{g2}, \cdots P_{gd}]$ (*gbest*).

In QPSO, the particles update according to the following equations:

$$mbest = (1/M)\sum_{i=1}^{M} P_i = [\sum_{i=1}^{M} P_{i1}/M, \sum_{i=1}^{M} P_{i2}/M, \cdots, \sum_{i=1}^{M} P_{ij}/M] \quad (12)$$

$$pp_{ij} = \phi P_{ij} + (1-\phi)P_{gj}, \phi = rand(0,1) \quad (13)$$

$$x_{ij} = pp_{ij} + \alpha |mbest_j - x_{ij}| \ln(1/u), u = rand(0,1) \quad (14)$$

where *mbest* is mean best position of particle swarm; pp_{ij} is a stochastic attractor of particle i that lies in a hyper-rectangle with P_{ij} and P_{gj} being two ends of its diagonal and moves following P_{ij} and P_{gj}; α is named as the contraction-expansion coefficient, which is the only parameter in QPSO and can be adjusted manually to control the speed of convergence.

3. APPLING DFNN TO THE ESTIMATION OF THE LENGTH OF GARMENT MARKING

3.1. Data Acquisition and Preprocessing

The literatures [5] and [6] suggest that the length of garment marking is intimately linked with garment specification and circumference, the width of the fabric, the number of layout and mixing index. The data in the article come from the literature [6], and select men's suit with more complicated pattern design as experimental swatch, the size-breakdown of men's suit is shown in Table **1**. Richpeace software was used to perform layout simulation. In the process of layout, every equipment layouts four times automatically and uses its mean value as the garment packing efficiency and the length of garment marking according to the difference of rules provided by the software for reducing the influence of artificial factors as far as possible. Experiment data provided by equidistant sampling method according to different combinations of garment specification under the condition of different width can be referenced [6].

Table 1.   Size-breakdown of men's suit cm.

Specification	Length	Bust	Sleeve	Shoulder	Cuff
80	72	98	57.5	43.8	13.5
84	74	102	59.0	45.0	14.0
88	76	106	60.5	46.2	14.5
92	78	110	62.0	47.4	15.0
96	80	114	63.5	48.6	15.5

The original data were firstly preprocessed in order to diminish the difficulty of fuzzy neural network training and balance the training parameters. The original data were scaled into the interval [0,1] by adopting linear transformation in this paper. Transformation formula is

$$Pn = (P - P_{min})/(P_{max} - P_{min}) \quad (15)$$

where P is the original data, Pn is normalized data, P_{min} is the minimum of P, P_{max} is the maximum of P.

We must de-normalize test and simulation after building DFNN model applied by normalized data. Transformation formula is

$$A = A_0(A_{max} - A_{min}) + A_{min} \quad (16)$$

where, A_0 is DFNN simulation output, A is de-normalized data, A_{min} is the minimum DFNN simulation output of original data, and A_{max} is the maximum DFNN simulation output of original data.

3.2. Optimizing Parameters of DFNN Based on QPSO

Since there are many related initial parameters whose values directly affect the performance of DFNN, repeated simulation experiments show that there is relatively sensitive influence of network performance on convergence parameter β, attenuation constant γ and the initial width parameter σ_0 of Gaussian membership function. Thus, β, γ and σ_0 are optimized and selected based on QPSO algorithm for speeding up training rate, other parameters are set directly. Concrete steps are as follows:

(1)   Initialize the particle swarm, give the initial value of determining parameters and β, γ and σ_0;

(2)   Use DFNN to calculate the predictor of the length of garment marking and average relative error function is used as fitness function, that is:

$$\text{Fitness} = (1/n)\sum_{i=1}^{n} |y_i - f(x_i)|/y_i \quad (17)$$

where y_i is target value, $f(x_i)$ is output of DFNN;

(3)   Calculate function value of each particle at the current position, including the location and fitness, if the corresponding fitness function value is less than the

minimum ever before, then update the local optimum position of particles;

(4) Compare the best fitness of each particle with global particle's fitness, if a certain particle's fitness is less than global particle's fitness, then update the global optimal position;

(5) Calculate *mbest* and a stochastic attractor of each particle, update new position of each particle;

(6) Judge whether they meet the termination conditions or not, if meet, then switch to (7), if not, switch to (2);

(7) Create a set of parameter values $(\beta, \gamma, \sigma_0)$ as the optimization results.
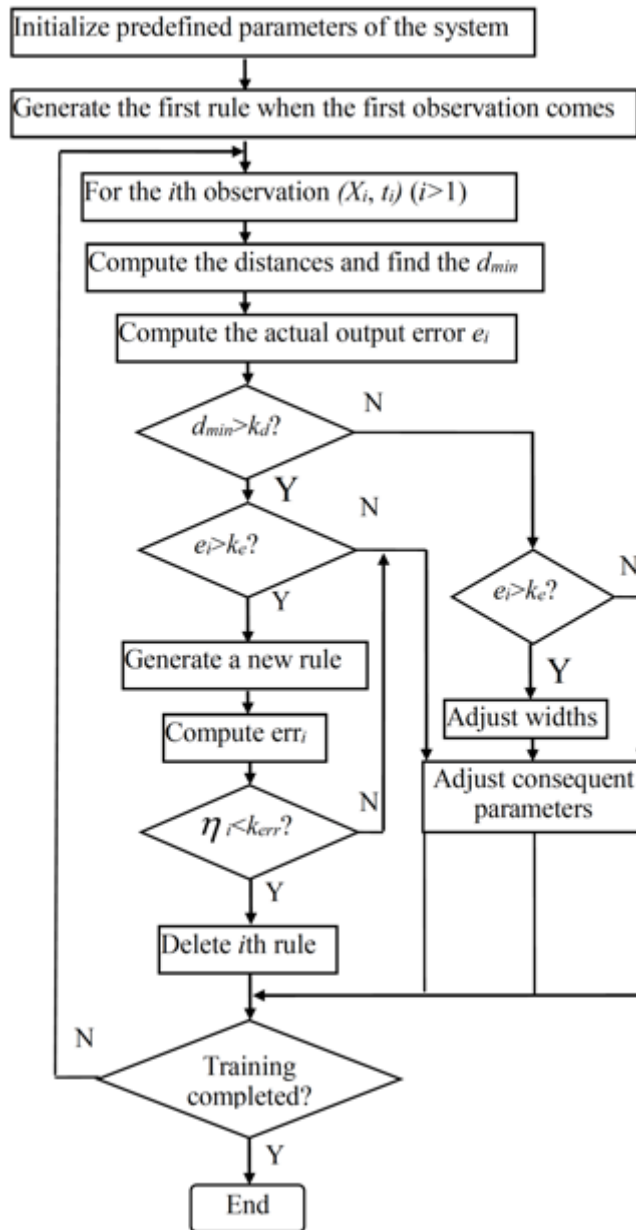
Fig. (2). Flowchart of the learning algorithm for the DFNN.

3.3. Simulation Results and Discussion

In order to carry out a direct comparison with the result of the literature [6], 42 groups of experimental data can also be divided into two groups. One group was used as a training data set, and another (the serial numbers are 3,7,10,14,19,23,27,31,35,40) was used as a testing data set. Related parameters values of DFNN directly adopted by the experiment are:

d_{max} =2; d_{min} =0.25; k =1.02; e_{max} =1.1; e_{min} =0.01; k_ω =1.01; k_{err} =0.00025;

Other three parameters values optimized by the above algorithm are:

β =0.095; γ =0.95; σ_0 =0.945.

Fig. (**3**) gives growth of fuzzy rules with the increase of input sample patterns in the process of algorithm implementation. Fig. (**4**) depicts fitting effect of optimized DFNN model during training. Fig. (**5**) is prediction effect of optimized DFNN model during testing. Fig. (**6**) gives four membership functional graphics generated by DFNN.
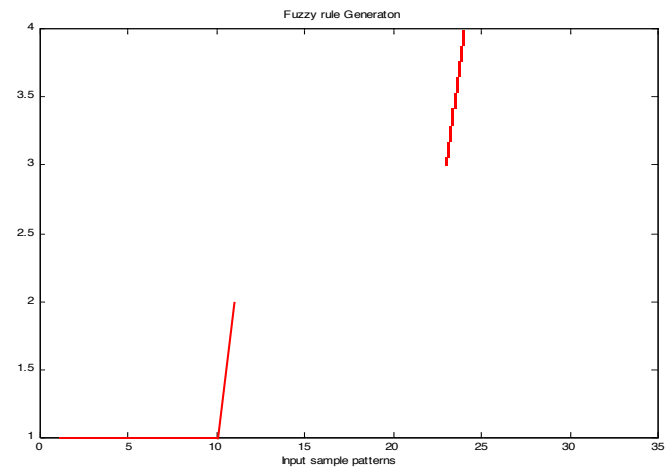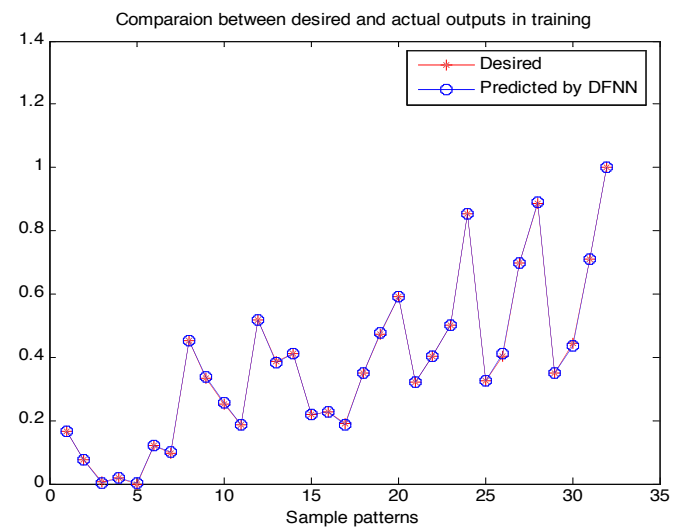

Fig. (3). Growth of fuzzy rules.

Fig. (4). Fitting effect during training.

Figs. (**7**, **8**) give scatter diagrams and fitted equations generated by comparing calculated values with actual values of test samples using BPNN model and DFNN model, respectively. The two figures show that fitted equation of

DFNN model is $y = 0.98x + 70.62$ and fitted equation of BPNN model is $y = 1.05x - 179.54$. Comparing with fitted equations of the two models, there are larger divergences between fitted equation of BPNN model and $y = x$ than those of fitted equation of DFNN model, demonstrating the higher accuracy of DFNN model intuitively.
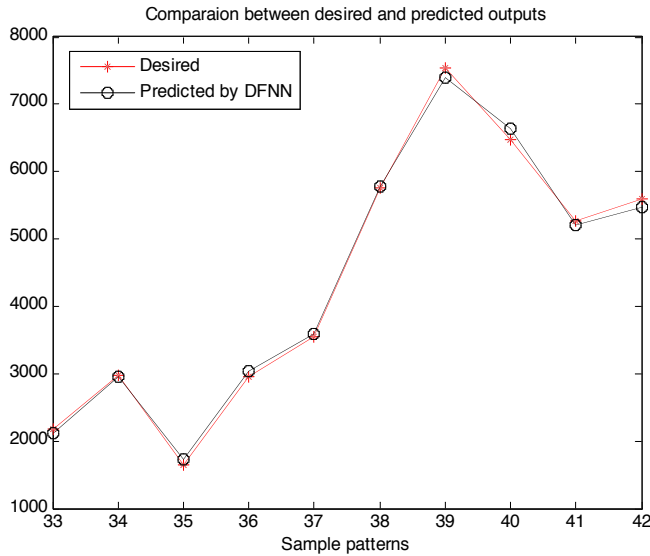

Fig. (5). Prediction effect during testing.

Table **2** shows the forecasting results using DFNN and BPNN models on three indices, absolute error, relative error and average relative error. As can be seen from the table, the accuracy of DFNN model based on QPSO optimal parameter is higher than the accuracy of BPNN model. The maximum relative error and average relative error between predicting outcomes and measured values of ten samples predicted by trained DFNN model are 5.11% and only 2.01%, respectively, which shows that DFNN model based on QPSO optimal parameter gives better predictions in comparison with BPNN model.

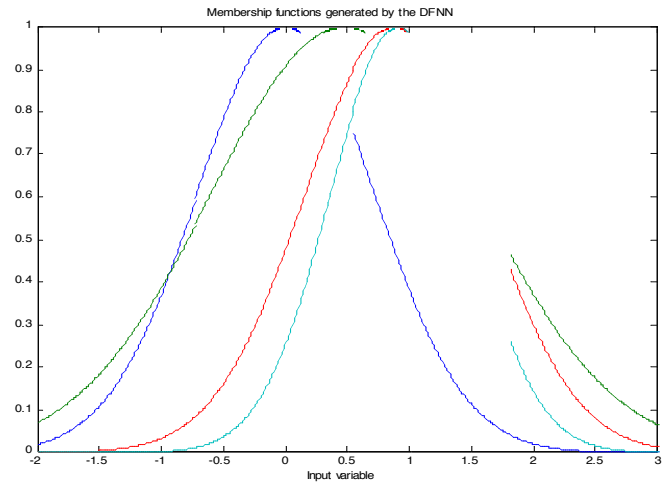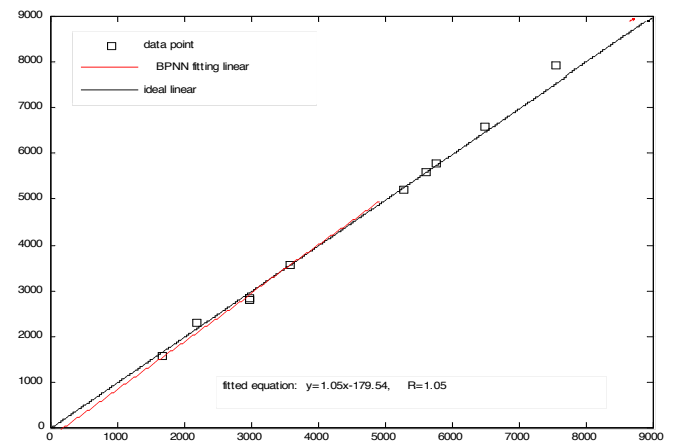**Fig. (6).** Membership functions generated by DFNN.

Fig. (7). Verifying results of test samples using BPNN.

4. CONCLUSIONS

This study developed a novel hybrid model based quantum-behaved particle swarm optimization and dynamic fuzzy neural networks model for the length of garment

Table 2.   Forecasting values of DFNN model and BPNN model.

No.	Experimental Value/mm	DFNN Algorithm			BPNN Algorithm		
		Predicted/mm	Absolute Error/mm	Relative Error/%	Predicted /mm	Absolute Error/mm	Relative Error/%
3	2171.57	2124.5	-47.0457	2.17	2324.85	153.28	7.058
7	2979.34	2959.5	-19.8147	0.67	2812.07	-167.27	5.614
10	1650.80	1735.1	84.2795	5.11	1586.35	-64.45	3.904
14	2957.21	3042.7	85.4843	2.89	2861.30	-95.91	3.243
19	3555.48	3594.2	38.7564	1.09	3569.30	13.82	0.389
23	5751.16	5782.4	31.2500	0.54	5799.87	48.71	0.847
27	7545.46	7392.7	-152.7368	2.02	7953.02	407.56	5.401
31	6484.13	6631.5	147.3452	2.27	6588.45	104.32	1.609
35	5261.37	5199.1	-62.3158	1.18	5243.63	-17.74	0.337
40	5589.35	5466.6	-122.7476	2.20	5615.49	26.14	0.468
Average relative error		2.01%			2.887%		

marking. The method can automatically acquire the nonlinear relationship between the length of garment marking and its influencing factor through learning the training data, and estimate the length of garment marking. Simulation experiments show that the method used DFNN to estimate the length of garment marking is viable. This method automatically determines fuzzy rules of fuzzy neural network, realizing online learning with high learning speed, and the prediction accuracy is superior to BPNN and the traditional multiple regression method. The model provides a new guiding principle to estimate the fabric consumption quickly and accurately and design optimal cutting scheme in the actual production for enterprises.
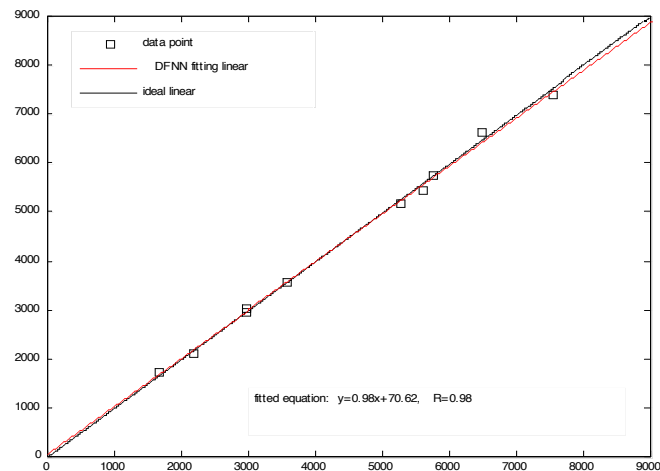

Fig. (8). Verifying results of test samples using DFNN.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

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