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A Novel NSNN Technique for the Estimations of TP Optical Properties

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***Abstract*—**This paper presents the optical property's estimations of touch panel (TP) film by using the nearly equivalent neural network (NENN) model. The NENN model is developed for solving the local minima leaning problem of conventional NN with fixed size. It is expected to obtain more accurate mapping between the input and output pairs of data. The estimations of chromatic aberration (*L, a, b* values) of TP film were simulated. The TP film's chromatic aberration and its all possible influencing factors in the evaporation process were studied and analyzed. The simulation results show that the NENN model indeed has the outperformance than conventional NN model. In other words, a more accurate intelligent estimator for the chromatic aberration of TP film could be developed. Based on this estimator, the technician could set the parameters of evaporation process in advance and the quality of chromatic aberration of TP could also be easily controlled.

Keywords*-estimati; touch panel; equivalent neural network; chromatic aberration***.**

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I. INTRODUCTION

Due to the powerful nonlinear mapping ability, NN has been widely employed into many fields such as signal prediction, decision making, fault diagnosis, pattern recognition and so on [1]-[4]. Basically, NN has the ability to derive the hidden information from complicated or imprecise data through a simple learning process. Mendal and McClaren (1970) defined that learning is a process by which the free parameters of a neural network are adapted through a process of simulation by the environment in which the network is embedded. The type of learning is determined by the manner in which the parameter changes take place [5].

In most of NN's applications, the supervised error back-propagation (BP) learning algorithm is commonly taken to perform the NN's learning process. The synaptic weights of NN are modified in proportion to the output error for achieving the desired objective. However, it is well known that the slow convergent speed and easily plunging into the local minima are two major lacks of the network with BP learning rule. The problem of local minimum learning will cause NN model to have an incomplete or ill learning condition and may make NN have the poor performance in its real-line operation. In order to improve the local minimum learning problem of NN, many methods have been proposed [6]-[12]. Some of them discussed the minima-free condition based on the point of learning environment of the network surrounded [7]-[9], [13]-[15]. Some of them used the evolutionary algorithms such as particle swarm optimization (PSO) and genetic algorithm (GA) to approach the optimal learning of network [16]-[18]. In fact, the most popular and easy method is to retrain the network by using different initial weights [19]-[20]. The local minimum condition can be observed from the network's performances and the best learning result is often selected while the network has the lowest output error.

Recently, TP has been used to many electronic appliances due to its convenience. For instance, television, mobile phone, computer and ticket vender are all equipped with TP. Generally, the manufacturing process of TP includes several steps which are injection, coating and printing. The quality of TP is completely determined by the well control of these manufacturing steps is successful or not [21]-[23]. In the coating process, the TP film's decoration is usually processed in the vacuum evaporator. But, the relevant control parameters of evaporator need to be set in advance by the full experienced technician to ensure the whole coating process could be accomplished well. Unfortunately, trail-and-error is still the common method taken by the technician in the real-line operation. It is known that the well evaporation process is determined by several factors such as the target composition, the layers and the thickness of coat and the speed of evaporation. These factors indeed affect the optical quality of TP film produced could meet the customer's request or not. The chromatic aberration (*L.a.b.* values) is one of the measures used to judge the quality of TP film. Its value is highly correlated with the factors mentioned and the relationship among them is very complicated and nonlinear.

In this research, a new technique named NENN model is proposed. NENN model is developed for searching the global minimum learning of NN with fixed size. The original supervised NN model is replaced by an appropriate high-order polynomial function. And, this high-order polynomial function could be treated as a multi-variable linear function and its parameters could also be easily obtained by using the linearly adaptive filter method. In this study, NENN model was used to estimate the chromatic aberration (*L.a.b.* values) of the TP decoration film. An artificial intelligent evaporation decision mechanism is expected to be developed in order to help the technician could easily and precisely set the control parameters for the film evaporation process. Section II describes the NN and NENN models. Section III presents the research simulations and the conclusion is given in Section IV.

II. NN & NENN MODELS

In the past three decades, NN has progressed through both conceptual innovations and implementation developments. The commonly well-known NN structure is the supervised multi-layer feed-forward network. The aim of NN's learning is to search the network connections (weights) which can accurately obtain the linear or nonlinear relationship between the input and output pairs of the training data. The NN's weights could be adjusted to minimize the cost (error) function defined. As

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mentioned above, the drawbacks associated with the error BP learning algorithm are its slow convergence and local minimum problem. The local minimum learning may result in a failed generalization of NN which could cause the poor performance in NN's real application.

In general case, a fixed size NN model is treated as the complete learning once the weights of network are convergent. However, such a condition cannot guarantee the trained NN could reach the global minimum error. Thus, the NENN model is proposed to verify the trained NN has the optimal learning or not. In our research, each neuron of the trained NN is substituted by an adequate polynomial function which can be generated by using the Sigma-Pi polynomial NN shown in Fig. 1 [24]-[25].

Here, we denote $X_k = [x_{0k}, x_{1k}, x_{2k}, \ldots, x_{nk}]$; $x_{0k} = 1$, as the k^{th} input pattern, then the output z_{jk} of the j^{th} sigma unit is given by

$$z_{jk} = \sum_{i=0}^{n} w_{ij} x_{ik} \tag{1}$$

The network output y_k could be expressed by

$$y_k = \prod_{j=1}^{h} z_{jk} \tag{2}$$

where h is the number of hidden nodes. From (1) and (2), the response of Sigma-Pi network can be expressed as a high-order polynomial function.

$$y_k = \prod_{j=1}^{h}\left(\sum_{i=0}^{n} w_{ij} x_{ik}\right) = c_0 + \sum_{i=1}^{n} c_i x_{ik} + \sum_{i=1}^{n}\sum_{j=1}^{n} c_{ij} x_{ik} x_{jk} + \cdots \tag{3}$$

where the coefficients (c_0, c_i, c_{ij}, …) are the generated terms of the network's weights w_{ij}

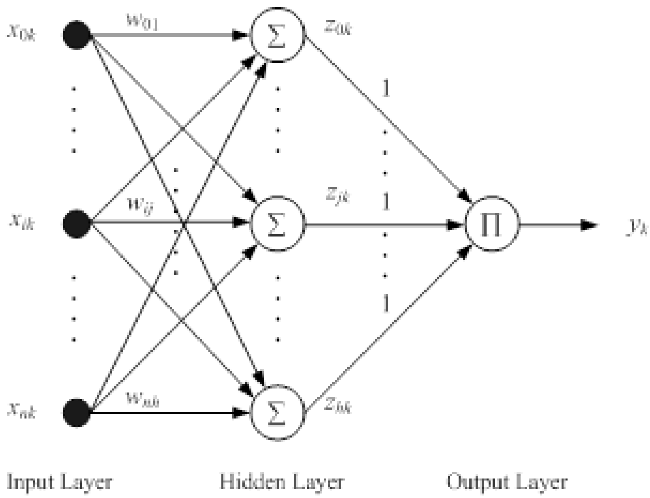

Figure 1. The diagram of Sigma-Pi network.

However, in the substitution process, the order of polynomial function for each neuron may not be the same and should be as small as possible. Each substitute polynomial function must have the nearly equivalent mapping behavior same as its corresponding neuron has. The whole illustrative diagram is shown in Fig. 2.

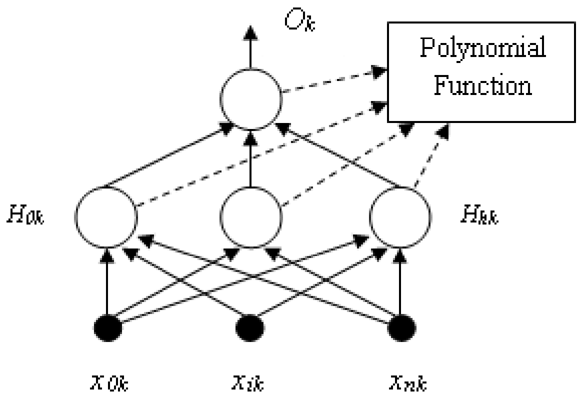

Figure 2. The illustrative diagram of NENN model.

In Fig. 2, we suppose all neurons of the original NN model have been substituted completely by a NENN model. Thus, the output (O_k) of NENN model can be expressed by a polynomial function which is derived as (4).

$$O_k = \Pi(\sum_{i=0}^{h} \alpha_i H_{ik}) = \alpha_0 + \sum_{i=1}^{h} \alpha_i H_{ik} + \sum_{i=1}^{h}\sum_{j=1}^{h} \alpha_{ij} H_{ik} H_{jk} + \cdots \tag{4}$$

where h is the number of the neurons in the hidden layer of the original NN. H_{ik} and H_{jk} denote the computed values of i^{th} neuron and j^{th} neuron in the hidden layer. $(\alpha_0, \alpha_1, \ldots, \alpha_{ij}, \ldots)$ are the coefficients of the polynomial function. By (3), the computed value of j^{th} hidden neuron can be expressed as a polynomial function of inputs.

$$H_{jk} = \Pi(\sum_{i=0}^{n} \beta_i x_{ik}) = \beta_0 + \sum_{i=1}^{n} \beta_i x_{ik} + \sum_{i=1}^{n}\sum_{j=1}^{n} \beta_{ij} x_{ik} x_{jk} + \cdots \tag{5}$$

where n is the number of neurons in the input layer, x_{ik} denotes the i^{th} input at time k. $(\beta_0, \beta_1, \ldots, \beta_{ij}, \ldots)$ are the coefficients of the function.

Clearly, a NENN model can be derived by (4) and (5) and it is expressed as (6).

$$O_k = \gamma_0 + \sum_{i=1}^{n} \gamma_i x_{ik} + \sum_{i=1}^{n}\sum_{j=1}^{n} \gamma_{ij} x_{ik} x_{jk} + \cdots \tag{6}$$

where $(\gamma_0, \gamma_1, \ldots, \gamma_{ij}, \ldots)$ are coefficients.

Once the NENN model is determined, the training data then can be used to retrain the NENN model for searching the optimal mapping between the input and output pairs of data. In fact, the optimal values of $(\gamma_0, \gamma_1, \ldots, \gamma_{ij}, \ldots)$ are able to be obtained by using the optimal filtering method. In this study, the least-mean-square (LMS) algorithm was used to find the

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values of $(\gamma_0, \gamma_1, \ldots, \gamma_{ij}, \ldots)$. In the retraining process, if the performance of NENN model is better than the original NN model, then we conclude that the original NN model is in the condition of local minimum learning. Otherwise, the original NN model presented has achieved its optimal learning.

III. SIMULATIONS

In our study, the data of decoration film with two layers coating were studied and simulated. Table I listed the example of data simulated. The variables of data include the value of quartz crystal (x_1), the rotation speed of holder (x_2), the substrate position of panel (x_3), Cr thickness (x_4), Cr_2O_3 thickness (x_5) and *L. a. b.* values of chromatic aberration. The complex relationships among *L. a. b.* values and their possible influencing factors are expected to be developed by NN and NENN models.

In order to demonstrate the feasibility of models used, four different data sets; Set-1, Set-2, Set-3 and Set-4, were randomly re-organized from the original data collected. For each data set, 100 points were used for NN's trainning and 44 points were used for testing. The mean absolute percentage errors (MAPE) is used to be the judgement for model's performance.

TABLE I. The example of simulation data.

x_1	x_2	x_3	x_4	x_5	Chromatic aberration		
					L	*a*	*b*
631	5	3	150	130	32.42	3.23	2.68
624	10	1	105	0	39.37	3.35	3.54
620	10	7	65	0	48.56	3.24	1.99
631	10	3	150	130	29.37	3.43	3.27
632	15	1	100	80	37.37	3.51	2.34
625	10	12	145	0	25.53	3.4	2.91
632	15	10	100	80	38.23	3.44	2.73
625	10	6	145	0	25.3	3.37	2.89

In fact, the rotation speed of holder, Cr thickness and Cr_2O_3 thickness had been concluded as three most important influencing factors for the chromatic aberration in our past researches [26]-[27]. Thus, only these three factors are considered in our simulations. Table II, Table III and Table IV present the estimated statistic errors of *L. a. b.* by NN model with size 3-4-1. All NN's simulation results are obtained by using the cross-validation method.

TABLE II. The MAPEs of *L* estimation by NN model.

L value	Training (%)	Test (%)
Set-1	1.62	1.77
Set-2	1.63	1.81
Set-3	1.55	1.64
Set-4	1.60	1.79
Avg.	**1.60**	**1.75**

TABLE III. The MAPEs of *a* estimation by NN model.

a value	Training (%)	Test (%)
Set-1	1.37	1.52
Set-2	1.48	1.65
Set-3	1.53	1.63
Set-4	1.58	1.61
Avg.	**1.49**	**1.60**

TABLE IV. The MAPEs of *b* estimation by NN model.

b value	Training (%)	Test (%)
Set 1	4.83	5.62
Set 2	4.99	5.73
Set 3	5.21	5.54
Set 4	5.33	5.72
Avg.	**5.09**	**5.65**

From above results, we could find that the average MAPEs for *L.a.b.* test data are 1.75%, 1.60% and 5.65%, respectively.

In NENN study, three well-trained NN models are used for *L. a. b.* simulations. We select the trained NN model of data Set-3 for *L* value, the trained NN model of data Set-1 for *a* value and the trained NN model of data Set-3 for *b* value. In order to determine the adequate order of NENN model, the behavior of individual neuron of these well-trained NN models are firstly approximated accurately by the polynomial NN. At last, the 6th order polynomial function is determined to be the structure of NENN model for *L.a.b.* simulations. The coefficients $(\gamma_0, \gamma_1, ..., \gamma_{ij}, ...)$ of NENN model shown as (6) were calculated by LMS algorithm. Table V lists the simulation results performed by NN and NENN models respectively for *L. a. b.* estimations.

TABLE V. The estimation errors of NENN model for *L.a.b.*

Data Set	NN		NENN	
	Training (%)	Test (%)	Training (%)	Test (%)
Set-3 (*L* value)	1.55	1.64	1.46	1.49
Set-1 (*a* value)	1.37	1.52	1.35	1.41
Set-3 (*b* value)	5.21	5.54	4.87	4.93

Obviously, the performances of NENN model are better than NN's. In order to desmonstrate the superiority of NENN model, data Set-1 to Set-4 of *L.a.b.* estimations were redone by NENN. Table VI, Table VII and Table VIII present the estimated statistic errors of *L. a. b.* by NENN model.

TABLE VI. The MAPEs of *L* estimation by NENN model.

L value	Training (%)	Test (%)
Set-1	1.53	1.58
Set-2	1.52	1.61
Set-3	1.46	1.49
Set-4	1.49	1.63
Avg.	**1.50**	**1.58**

TABLE VII. The MAPEs of *a* estimation by NENN model.

a value	Training (%)	Test (%)
Set-1	1.35	1.41
Set-2	1.40	1.46
Set-3	1.38	1.44
Set-4	1.43	1.41
Avg.	**1.39**	**1.43**

TABLE VIII. The MAPEs of *b* estimation by NENN model.

b value	Training (%)	Test (%)
Set 1	4.86	5.01
Set 2	4.78	5.31
Set 3	4.87	4.93
Set 4	4.92	5.34
Avg.	**4.86**	**5.15**

Again, the NENN model has outperformances than NN model.

IV. CONCLUSION

In this research, the chromatic aberration (*L.a.b.*) estimations of TP decoration film by using the nearly equivalent NN (NENN) model are presented. The relationship between the chromatic aberration and its influencing factors can be effectively developed by the model proposed. The simulation results obviously show that the performances of NENN are better than conventional NN. This study evidences that the NN model with BP learning rule based on steepest descent algorithm indeed easily makes network get stuck in the local minimum. On the contrary, the NENN with simple LMS tuning method can easily reach the optimal approximation and develop more accurate mapping model. It is concluded that the technique proposed is quite promising in the real application of NN. However, in order to easily have the optimal approximation, the order of NENN model should be appropriate and as small as possible.

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REFERENCES

[1] S. Chen, S. Billings, and P. Grant, “Non-linear system identification using neural networks,” *International Journal of Control*, vol. 51, pp. 1191-1214, 1990.

[2] A. Khotanzad, R. C. Hwang, A. Abaye, and D. Maratukulam, “An adaptive modular artificial neural network: Hourly load forecaster and its implementation at electric utilities,” *IEEE Transactions on Power Systems*, vol. 10, pp. 1716-1722, 1995.

[3] B. Zhang, M. Fu, H. Yan, and M. A. Jabri, “Handwritten digit recognition by adaptive-subspace self-organizing map (ASSOM),” *IEEE Transactions on Neural Networks* , vol. 10, no. 4, 1999.

[4] T. Li, Q. Zhang, R. York, “Artificial neural networks for electronic nose measurement of odor,” *ASAE Annual International Meeting*, pp. 4289-4298, 2004.

[5] J. M. Mendel and R. W. McLaren, "Reinforcement learning control and pattern recognition systems", in J. M. Mendel and K. S. Fu, editors, Adaptive Learning and Pattern Recognition Systems: Theory and Applications, pp. 287-318. Academic Press, New York, 1970.

[6] B. Cetin, J. Burdick, and J. Barhen, “Global descent replaces gradient descent to avoid local minima problem in learning with ANN,” *Proceedings of IEEE International Conference on Neural Network*, vol. 2, pp. 836-842, 1993.

[7] X. H. Yu and G. A. Chen, “On the local minima free condition of backpropagation learning,” *IEEE Transactions on Neural Networks*, vol. 6, pp. 1300-1303, 1995.

[8] D. S. Huang, “The local minima-free condition of feedforward neural network for outer-supervised learning,” *IEEE Transactions on System, Man, and Cybernetics-Part B: Cybernetics*, vol. 28, no. 3, pp. 447-480, June 1998.

[9] K. Fukumizu and S. I. Amari, “Local minima and plateaus in multilayer neural networks,” *Artificial Neural Networks, Conference Publication* no. 470, pp. 597-602, Sept., 1999.

[10] W. Huyer and A. Neumaier, “Global optimization by multilevel coordinate search,” *Journal of Global Optimization*, vol. 14, pp. 331-335, 1999.

[11] I. Sprinnhuizen-Kuyper and E. Boers, “A Local Minimum for the 2-3-1 XOR Network,” *IEEE Transactions on Neural Networks*, Vol. 10, No. 4, pp. 968-971, 2002.

[12] I. N. Jordanov and T. A. Rafik, “Local minima free neural network learning,” *Proceedings of 2nd IEEE International Conference on Intelligent Systems*, pp. 34-39, June, 2004.

[13] T. Poston, C. N. Lee, Y. Choie, Y. Kwon, “Local minima and back propagation,” *International Joint Conference on Neural Networks*, vol. 2, pp. 173—176, 1991.

[14] X. H. Yu, “Can backpropagation error surface not have local minima,” *IEEE Transactions on Neural Networks*, vol. 3, pp. 1019—1021, 1992.

[15] M. Gori, A. Tesi, “On the problem of local minima in backpropagation,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 14, pp. 76—86, 1992.

[16] K. A. Toh, “Deterministic global optimization for FNN training,” *IEEE Transactions on Systems, Man and Cybernetics, part B*, vol. 33, pp. 977—983, 2003.

[17] R. S. Sexton, J. N. D. Gupta, “Comparative evaluation of genetic algorithm and backpropagation for training neural networks,” *Information Sciences*, vol. 129, pp. 45-59, 2000.

[18] E. Cantu-Paz, C. Kamath, “An empirical comparison of combinations of evolutionary algorithms and neural networks for classification problems,” *IEEE Transactions on Systems, Man and Cybernetics, part B*, vol. 35, pp. 915—927, 2005.

[19] Y. R. Park, T. J. Murray, C. Chung, “Predicting sun spots using a layered perceptron neural network,” *IEEE Transactions on Neural Networks*, vol. 7, pp. 501—505, 1996

[20] M. S. Iyer, R. R. Rhinehart, “A method to determine the required number of neural-network training repetitions,” *IEEE Transactions on Neural Networks*, vol. 10, pp. 427-432, 1999.

[21] N. L. Dmitruk; A.V. Korovin, ”Generalized analytical model for the calculation of light transmittance through a thin conducting film,” *Thin Solid Films*, vol. 484, no. 1-2, pp. 382-388, 2005.

[22] K.Wang, H. Z. Jia; G. Z. Xia, “Determination of optical parameters in thin films by transmittance spectra,” *Spectroscopy and Spectral Analysis*, vol. 28, no. 11, pp. 2713-2716, 2008. Language: Chinese

[23] G. Z. He; X. L. Yao,“Properties of ITO thin films prepared by APS assisted EB Evaporation”, *Proceedings of the International Society for Optical Engineering*, pp. 6831, 2008.

[24] D. J. Huang, C. C. Huang, Y. J. Chen, H. C. Huang, S. W. Chen, R. C. Hwang, "System identification of TP film evaporation by using nearly equivalent NN model", *The Fourth International Conference on Genetic and Evolutionary Computing*, pp.118-121, 2010.

[25] C. C. Huang, *A Novel Neural Network Technique and Its Applications*, Ph.D. Thesis, I-Shou University, Taiwan, 2011.

[26] Y. J. Chen, P. T. Hsu, S. M. T. Wang, C. Y. Shen, S. W. Chen, R. C. Hwang, "An intelligent data mining technique for the estimations of TP film’s chromatic aberration", *Proceeding of 2013 2nd International Symposium on Instrumentation and Measurement, Sensor Network and Automation (IMSNA))*, pp.727-730, 2014.

[27] P. T. Hsu, *The Studies of Data Mining by Using Neural Network*, Master Thesis, I-Shou University, Taiwan, 2012.