Appl. Math. Inf. Sci. 6 No. 2S pp. 561S-565S (2012)

Applied Mathematics & Information Sciences
An International Journal

Enhancing BEF Luminance for TFT-LCD Industries using the Hybrid Approach of Prediction and Optimization Techniques

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Received July 15, 2011; Revised Aug. 15, 2011; Accepted Sep. 2, 2011
Published online: 1 January 2012

Abstract: A Backlight Module is the main source supply of liquid crystal display components. Its power consumption is about half the liquid crystal display. Among the Backlight Module, BEF / DBEF enhances luminance 50% to 100%. Therefore BEF (Brightness Enhancement Film) / DBEF (Dual Brightness Enhancement Film) becomes the main critical component of Backlight Module. The assurance of sustaining balance for both the high luminance with low consumption is a challenging research issue for industries. Although in the past there many research works have been done about the light guide plate and light source of the Backlight Module, however rare research has been reported about enhancing the brightness film based on constrained production costs. Since there are many manufacturing factors influencing BEF's luminance, in this study we attempt to find out the suitable manufacturing control parameters by employing the hybrid approach of both prediction and optimization techniques. The neural network is used to learn the experimental data set from real-time collected operation data. After the BEF prediction model is constructed and tested with acceptable prediction performance, the genetic algorithms (GA) is applied to the prediction model to find out the most suitable operation control parameters that produce the expected BEF luminance. The experimental results show that the proposed approach is able to increase the BEF luminance up to 12% with competitive strength and potentials of manufacturing costs reduction.

Keywords: Liquid crystal display, neural networks, genetic algorithms, bright enhancement film.

1 Introduction

Current PCEPs (portable consumer electronic products) are expected with low power consumption and longer usage time. As one of the indispensable components of PCEP, market trend demands for TFT-LCD's (thin film transistor liquid crystal display) features light, thin, short, small forms with better quality and low price. Due to TFT-LCD itself does not glow, backlight module is its main component for the supply of uniform light source so that it can properly displays images. Liu & Wang [1] pointed out the most costly core component of backlight module are bright enhancement film (BEF), light guide plate (LGP), and cold cathode fluorescent lamps (CCFLs).

Since BEF manufacturing cost is about 37% of the backlight module that comprises 25% of TFT-LCD material cost, there is no denying that BEF plays an important role of the cost reduction for TFT-LCD manufacturing. On the other hand, backlight module costs 50% of TFT-LCD's power consumption, thus energy-saving feature becomes the ultimate resort for TFT-LCD products. The trade-off between high BEF luminance and low power consumption becomes a crucial issue in practice. Global backlight module market reached $1.4 billion Chang [2] in 2006, while reached 5.2 million units in 2009 and over 590 units in 2010 [3]. Backlight module can be used in the eBook, TFT-LCD, smart phones, and other information on consumer products. As the main device of backlight module for luminance, BEF's becomes the key factor for product competitiveness in the global market. As more and more companies get into the BEF area, enhancing the BEF luminance is the critical way for a company to succeed in the rigorous market.

In order to satisfy customer's requirements in various sizes, specifications, and functions, the techniques may vary based different needs. Usually BEF is manufactured through various processes with different control parameters that are tuned using trial and error. BEF performance generally depends on 32 machining parameters such as machine speed, gluing speed(x3), coiling length, and etc. To determine suitable values for the parameters is a challenging work that involves numerous adjustments that may consume voluminous resources including human labor, materials, and time. This research aims to tackle these problems by applying a prediction model developed by the means of neural nets to establish relationship between control parameters and BEF luminance as the process response. Furthermore, an attempt is made to optimize the BEF luminance prediction model using Genetic Algorithm (GA).

2 Related Works

In an era of global competition and rapid growth of science and technology, computer, communication and consumer electronics (3C) manufacturing have become the world's most rapid growing industries. Among these 3C industry products, TFT-LCD display device is even more essential in recent years. Liu & Wang [1] further pointed out that among all the TFT-LCD display devices, backlight module is a one of the most important components. In general, backlight module is composed of light source, light guide plate, reflector, diffuser, P-S converter, and BEF Optical components. Light source is expected be with high luminance and long life characteristics. Presently there are different types of light sources including CCFLs, hot cathode fluorescent lamps (HCFLs), light emitting diode (LED). Kim & Chung [4] indicated that CCFLs is the most prevalent in exiting markets, while white LED has gradually replacing CCFLs for it features low heat, power saving, long life, small size, environmental protection and other advantages.

BEF is also called prism film for its functionality is to coagulate the light rays and improve the front luminance via light refraction and reflection. Regularly backlight module needs two pieces of BEF to mutually conglomerate the luminance in a vertical way [5]. Formation is the most important stage in the entire BEF manufacturing process. Formation machining depends on effective ultraviolet glue spreading and picture forming by ultraviolet light exposure control. There are some research works related to the BEF quality improvement. For example, Cheng and Cheng [5] spited light guide plate into subdivisions with even ray density. Li et al. [6] applied neural nets to construct prism-type LGP design model using GA approach. This result has simplified and overcome the complicated design problems of the traditional way.

An artificial neural network (ANN), usually called neural nets (NN), is a mathematical model or computational model that is biologically inspired and has been widely applied to various prediction domains [7]. Among various types of neural nets topology, back-propagation neural-network (BPN) is the most widely applied technique with [6]. BPN has decent leaning performance with fast recall rate and fault tolerant characteristics. BPN is a particular type of neural network model known as a supervised learning algorithm. The BPN approach is well known and widely applied. Its applications include robotic manipulators control [8], customer classification [9], export success classification [10] and etc.

Optimization is the process of finding the optimum from a set of candidate solutions. It is usually employed when the problem structure is complex or there are millions of possible solutions. Optimization is divided into two classes: global and local ones. Global optimization finds the best solution from the set of all candidate solutions. It always finds a better solution regardless of the starting search point. Local optimization finds the best solution starting from the surrounding solutions to the nearer neighbor solutions. The final solution depends heavily on the starting point in a search for the optimum solution. This strategy is usually called a Descent Algorithm or a steepest descent strategy.

The GA, developed by Holland [11], is an optimal mechanism that mimics the genetic evolution of species. The GA deals with a population of solutions rather than with single solutions. It is one of the fast searching and practical approach that has been applied to various optimization problems. In general the GA contains reproduction, crossover, and mutation procedures to precede evolutionary computation.

The GA is a procedure for modeling genetic evolution and the natural selection processes. The basic GA consists of several components including the number of chromosomes in a generation, a 'fitness' evaluation unit, and genetic operators for 'reproduction', 'crossover' and 'mutation'. Initially a set of number strings generated by the random number generator is treated as a candidate solution for the optimization problem being addressed. Associated with each string is a fitness value that measures the quality of the candidate solution. The aim of the genetic operators is to transform the set of strings into sets with fitness values. In essence the procedure randomly selects highly fit individuals and their chromosomes to generate better offsprings within the new population. The unfit are eliminated while the fittest survive to contribute genetic material to the subsequent generations.

Zhang et al. [7] applied neural nets approach to build an intelligent model for the production of Polymer polypropylene resin, based on which GA was applied to find out the best input values for neural nets model. Both neural nets and GA are able to compliment with each other in finding out optimum solution, in this work we plan to integrate both of them to aid the manufacturing process in improving BEF luminance.

3 The Proposed Method

According to the system framework shown in Figure 1, BEF production data was collected for constructing the prediction model using neural nets. After the model has built and evaluated with acceptable performance, neural nets becomes the evaluation function of GA. GA attempts to find out the most suitable control parameters via evaluating the fitness values (i.e., BEF luminance) by neural nets. Subsequently, the GA produces the most decent parameters according to the expected BEF luminance outcome value.

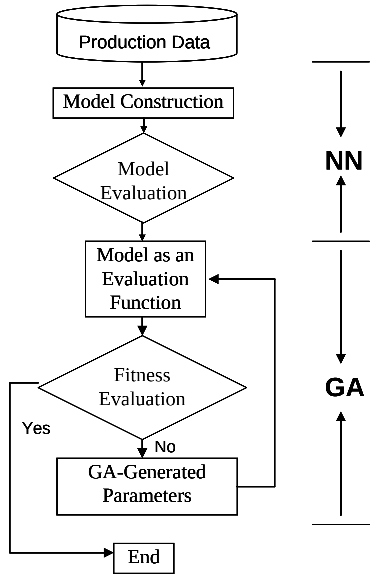

Figure 3: A Framework of Integration NN with GA.

4 The Experiments

This research collected 443 real on-line production data with 32 control variables from one ABC TFT-LCD manufacturing company in Taiwan. After deleting some constant input values, there are 7 control variables left as indicated in Table 1 including blank luminance (x1), core machine speed (x2), gluing speed (x3), coilng length (x4), left UV lamp strength (x5), central UV (x6) , right UV lamp strength (x7), and BEF luminance (Y), with their min and max values ranges.

Since those control parameters vary in scales, normalization process is then applied to these values before constructing prediction models. The normalization is done using (4.1). In order to examine and compare the effectiveness of the prediction models, we employ linear regression, regression tree approaches other than neural nets. Further, to avoid data sampling bias three-fold cross validation is applied for these experiments. F1, F2, F3 are the three different data sets generated for experiments.

$$(4.1)\ x_{new} = \frac{x_{old} - x_{\min}}{x_{\max} - x_{\min}}$$

As can be seen in Table 2, both mean absolute error (MAE) and root means squared error (RMSE) in training and testing stages are demonstrated with three-fold cross validation. The lower the values for MAE and RMSE, the better are the performance of the proposed approach. Among the three prediction approaches, the neural net outperforms linear regression and regression tree approaches in both training and testing stages. In the testing stage, neural nets mean MAE and RMSE for data sets F1, F2, and F3 are 23.71 and 43.98, which indicate both accuracies are within acceptable scales.

Table 1. Descriptive Statistics of Variables

Variable	Independent							Dependent
	x_1	x_2	x_3	x_4	x_5	X_6	x_7	y
Min.	3648	7	3.8	345	386	439	384	5138
Max.	5726	8	12	380	963	1146	879	5922

Table 2. MAE and RMSE for Different Models

Stage	Dataset	MAE			RMSE		
		LR	NN	RT	LR	NN	RT
Training	F1	76.96	19.24	31.02	28.28	28.28	55.70
	F2	23.27	19.81	19.73	33.42	29.05	31.23
	F3	73.49	23.78	32.71	124.69	30.47	57.93
	Mean	57.91	20.94	27.82	62.13	29.27	48.29
Test	F1	73.03	18.61	34.21	84.59	26.80	52.98
	F2	40.13	23.83	27.73	224.41	59.58	62.20
	F3	72.70	28.68	31.32	89.61	45.55	46.77
	Mean	61.95	23.71	31.09	132.87	43.98	53.98

Table 3 shows the estimated BEF luminance data after feeding the parameters determined by GA into the well trained neural nets. The range for expected BEF luminance is set from 5200 to 5900 with the interval of 100. The MAE and RMSE for the 8 experiments are 0.0014 and 0.0051 respectively, which show that the difference between real and expected BEF luminance and indicate the proposed approach is acceptable and practical.

Table 3. BEF Production Control Parameters

Variables Being Explored							Predicted BEF Luminance	Expected BEF Luminance
x_1	x_2	x_3	x_4	X_5	x_6	x_7	Y	Y'
3672	8	5.72	371	438	863	516	5200.0002	5200.0000
3985	7	8.63	352	437	770	823	5299.9980	5300.0000
4030	7	5.62	348	619	886	803	5400.0011	5400.0000
4128	7	6.79	369	583	639	505	5500.0006	5500.0000
4128	7	4.22	350	697	757	386	5600.0016	5600.0000
4013	8	3.88	350	444	891	536	5699.9960	5700.0000
4373	7	9.13	364	791	529	530	5799.9991	5800.0000
4755	7	10.40	349	660	555	780	5900.0008	5900.0000

5 Conclusions

Previous approach in BEF machining is based on trial-and-error tuning that is difficult to assure for its effectiveness, efficiency, and financial economics. In this work, an attempt is made to determine the optimal parameters for BEF production under varying conditions through the use of neural nets prediction and the GA parameters searching. The experiment findings have been applied into production lines and shown the expected outcomes closely match the real ones with stable performance. Since there are many factors could result in different luminance performances in various manufacturing stages, this study has focused on investigating and employing those main control factors affecting the TFT-LCD BEF luminance. It also known that there are dissimilar parameters settings at different stages of TFT-LCD manufacturing process. None the less, the application of combining neural nets and GA to determine the optimum control parameters is the unique and feasible approach. We do believe not only the BEF luminance is the concerns of selecting appropriate methodology, but also the time and efforts required to construct the prediction and optimization models are important as well. In this research we don't consider the costing issue and resulted quality such as TFT-LCF lifetime in terms of those adjustable factors. Potential research can be further explored in the future.

Acknowledgements

This research was supported by the National Science Council of Taiwan, Republic of China, under contract no. NSC99-2410-H-155-036-MY3.

References

[1] Liu, Y.H. and Wang, S.C., An FPGA-Based Dimmable CCFL Driving System for TFT-LCD Backlight, *IEEE Region Annual International Conference*, No. 4142200, 2007.

[2] Chang, W.S., Review and Forecast of the Global Backlight Module Industry, *Industrial Economics and Knowledge Center Report*, Industrial Technology Research Institute, (2006).

[3] zgcysddy, 2011-2015 Global and China Backlight Module, http://www.zgcysddy.com/html/YingWenBaoGao/ZongHeYingWen/18296.html, data accessed 2011/8/14.

[4] Kim, I. and Chung, K., Wide Color Gamut Backlight from Three-Band White LED, *Journal of the Optical Society of Korea*, Vol. 11, Issue. 2, (2007), 67-70.

[5] Cheng, Y.C. and Cheng, C.A., A Novel Driver Circuit for Multiple Cold-Cathode Fluorescent Lamps of TFT-LCD Backlight Modules, *Conference Record-IAS Annual*

Meeting (IEEE Industry Applications Society), (2008), 1-5.

[6] Li, C.J., Fang, Y.C. and Cheng, M.C., Study of Optimization of a TFT-LCD Light Guide Plate with Neural Network and Genetic Algorithm, *Optics Express*, Vol. 17, No. 12, (2009), 10177-10188.

[7] Zhang, Y., Xu, J., Yuan, Z., Xu, H. and Yu, Q., Artificial Neural Network-Genetic Algorithm Based Optimization for the Immobilization of Cellulase on the Smart Polymer Eudragit L-100, *Bioresource Technology*, Vol. 101, Issue 9, (2010), 3153-3158.

[8] KÃÃker, R., Design and Performance of an Intelligent Predictive Controller for a Six-degree-of-freedom Robot Using the Elman Network, *Information Sciences*, Vol.176, No.12, (2006),1781-1799.

[9] Kaefer, F., Heliman, C.M. and Ramenofsky, S.D.A, Neural Network Application to Consumer Classification to Improve the Timing of Direct Marketing Activities, *Computers and Operations Research*, Vol.32, No.10, (2005),2595-2615.

[10] Smith, D., A Neural Network Classification of Export Success in Japanese Service Firms: Performance Predictability and Determinant Impact, *Services Marketing Quarterly*, Vol.26, No.4, 95, (2005).

[11] Holland, J.H., Adaptation in Natural and Artificial System, Ann Arbor: The University of Michigan Press, (1975).

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