PREDICTION OF EXTINCTION RATIO’S TEMPERATURE COMPENSATION TABLE USING NEURAL NETWORK

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A dissertation submitted in partial fulfillment of the
requirements for the award of the degree of
Masters in Computer Science

School of Computing
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SEPTEMBER 2018

ACKNOWLEDGEMENTS

I would like to show my gratitude to my research supervisor, Assoc. Prof. Dr. Siti Zaiton Bt. Mohd Hashim, for her valuable inputs and assistance in several techniques, methods and shared wisdom for the completion of this paper.

This research paper was sponsored by Finisar to which I am thankful for. To Finisar staffs and employees, Jimmy Ling, thank you for initiating this Masters program. To Evelynn Soh Wan Ting, thank you for assisting us on the way. To my immediate supervisor, Marjo Dasmarinas and manager, Surashrajan Balakrishnan, thank you for allowing me to use Finisar resources for this paper.

Lastly, thank you to my beloved parents for continuously guiding and supporting me. To my love, John Eric, for the full support, patience and understanding, I express my greatest gratitude.

ABSTRACT

The conventional way of modeling extinction ratio's (ER) temperature compensation table of a transceiver module results to high manufacturing testing time, thus gives an issue in manufacturing line which is low UPH (Units per hour). The conventional way is through manual temperature cycling and through an algorithm which is step search. This uses an expensive time with low UPH. In an ER temperature compensation table, several TOSA and module parametric values affect it. Each of these parameters were studied and used to feed the network. This work aims on determining the best parameters that will produce AC bias based on relevant AC properties, developing an MLP ANN model that utilizes and identifies parameters in order to predict AC bias value which will be used in generating ER temperature compensation table, and lastly, modeling an artificial neural network that predicts ER temperature compensation table to boost up UPH. Several experiments were performed to select the best parameters to produce AC bias based on relevant AC properties and these are all TOSA data and Module_ER_at_80, which includes a total of 26 parameters. In addition to this, optimum UPH is obtained using these parameters at 2.44. And the MLP ANN model with 23 number of neurons in hidden layer was developed to obtain the highest possible neural network performance which is having 2.44UPH, +/-3 DAC counts distribution, ˜8.7 MSE, and ˜0.93 r-square.

ABSTRAK

Cara konvensional untuk mengira nisbah (ER) suhu adalah dengan membahagikan nisbah (ER) dengan jumlah pengurangan hasil modul transiver kepada masa ujian perkilangan yang tinggi. Situasi ini akan memberi masalah terhadap jumlah pengeluaran yang rendah UPH (Unit per jam). Cara konvensional terbaik adalah dengan melalui kaedah putaran suhu manual dan melalui pengiraan algoritma . Cara ini menggunakan masa yang lama dengan UPH yang rendah. Setiap jadual pengurangan suhu ER, ia melibatkan nilai TOSA dan parameter tertentu. Setiap parameter ini dikaji dan digunakan untuk memberi hasil kepada talian rangkaian. Langkah ini bertujuan untuk menentukan parameter yang terbaik untuk menghasilkan "ACBias" berdasarkan ciri- ciri AC yang relevan, pembangunan model MLP ANN yang menggunakan dan mengenal pasti parameter untuk meramalkan nilai "ACBias" yang akan digunakan dalam menjana suhu nisbah ER dan akhir sekali, model rangkaian neural buatan yang meramalkan Rajah pampasan suhu ER untuk merangsang UPH. Beberapa eksperimen dilakukan untuk memilih parameter terbaik untuk menghasilkan kecenderungan AC berdasarkan ciri-ciri AC yang relevan dan ini adalah semua data TOSA dan Module_ER_at_80, yang merangkumi sejumlah 26 parameter. Sebagai tambahan kepada ini, UPH optimum diperoleh menggunakan parameter ini pada 2.44. Dan model MLP ANN dengan 23 bilangan neuron dalam lapisan tersembunyi telah dibangunkan untuk memperoleh prestasi rangkaian neural tertinggi yang mempunyai 2.44UPH, +/- 3 DAC pengagihan, ˜8.7 MSE, dan ˜0.93 r-square.

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LIST OF ABBREVIATIONS

AC	-	Alternating Current
ANN	-	Artificial Neural Network
DC	-	Direct Current
ER	-	Extinction Ratio
ERTC_TX	-	Extinction Ratio Temperature Compensation TX
FINAL_TX	-	Final Transmitter testing
FW	-	Firmware
LDI	-	Laser Driver Current
MLP	-	Multi-Layer Perceptron
MSA	-	Multi-Source Agreement
MSE	-	Mean Square Error
PA	-	Point Adaptation
PCBA	-	Printed Circuit Board Assembly
ROSA	-	Receiver Optical Sub-Assembly
RX	-	Receiver
SLP	-	Single-Layer Perceptron
SMSR	-	Side Mode Suppression Ratio
TDL	-	Time Delay Lines
TX	-	Transmitter
TOSA	-	Transceiver Optical Sub-Assembly
UPH	-	Unit per Hour

CHAPTER 1

INTRODUCTION

1.1 Introduction

A transceiver module consists of two Optical Sub Assembly (OSA), one for Transmitter Optical Sub Assembly (TOSA) and another for Receiver Optical Sub Assembly (ROSA). Test data for these two OSAs should be passing data sheet specifications before assembled into a transceiver module. Once assembled, the whole transceiver module is subjected into parametric testing and should also be meeting data sheet and its Multi-Source Agreement (MSA) specification before shipping the parts to customer.

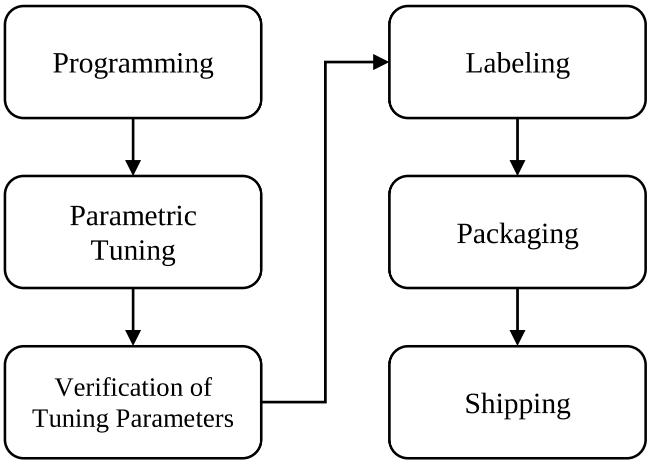

Figure 1.1: Optical Transceiver Manufacturing Process

In an optical transceiver module testing, there are several processes as shown in figure 1.1, such as programming, parametric tuning and verification, labeling, packaging, and then shipped to customer.

During programming, the transceiver module is programmed with its firmware, its name which is what we call serial number, its family which is what we call part number and several identities as well like manufacturing date and Finisar's company name. Then, the transceiver module is tuned to target several parameters based on its datasheet, these parameters are verified on the next process. Once it passed these tests, the unit is labeled with a printed barcode sticker that will contain its identity, then the unit is packaged together with the other units and shipped to customer. Let's concentrate more on parametric tuning and verification which is discussed on the next paragraphs.

In parametric tuning, an optical transceiver module is tuned to generate two temperature compensation tables. These are laser current and Extinction Ratio (ER) temperature compensation tables. In generating a table for extinction ratio, module is subjected to three temperatures. At each temperature a Direct Current (DC) bias value is determined for a targeted laser current value and Alternating Current (AC) bias value is determined for a targeted extinction ratio. For some optical transceiver modules, there is also a different table for different voltage levels.

The next test process after parametric tuning is verification of tuning parameters where the tuned parameters and temperature compensation table is verified and tested on different temperature settings and voltage settings for its correctness. The accuracy in determining the AC bias value for extinction ratio should be high in order to have lesser failures during verification test process.

1.2 Background of the Problem

To generate an extinction ratio temperature compensation table, the module will be subjected to three temperatures, one is room temperature and the other two are extreme temperatures such as cold and hot temperature. One issue here is it takes a long time to ramp a temperature from cold to hot temperature. Another issue is the generation of extinction ratio temperature compensation table which also takes time which will be discussed in the next paragraphs.

To target a certain ER per temperature, the current algorithm is through step search. In step search, a default AC bias value is firstly pumped into the module, then the ER is read out, if the ER is higher than the targeted value, then the AC bias value is lowered down through a certain value of step, if ER is lower than the targeted value, then ER is increased through a certain value of steps, until the ER is targeted.

By doing step search, it takes an average of 126 seconds to target an ER value. If there are three temperatures where we need to target ER plus two voltage settings, then that will take 630 seconds per module. If Finisar produces 100 optical transceiver module per week per test station, then it takes 63,000 seconds of step searching per week.

In a manufacturing company, units per hour (UPH) is very important as it defines the manufacturing company's efficiency. UPH is calculated by dividing the number of units produced in a day by the hours in the workday (Parrie, 2005). If we have 10 test stations, for a 100 unit output per week per test station, then UPH is 5.96. The struggle in a manufacturing company is to get the UPH increased as much as possible to boost up the company's efficiency, and the best way to do this is to reduce manufacturing testing time which will be one of the major aim of this research.

1.3 Problem Statement

The conventional way of modeling extinction ratio's temperature compensation table of a transceiver module results to high manufacturing testing time, which results to a ***low UPH (Units per hour)***. To generate a table is through manual temperature cycling and through an algorithm which is step search. This uses an expensive time with low UPH.

There are several AC and DC for both TOSA and module parameters that affects the ER and the proposed alternative solution is an ANN that predicts each AC bias in an ER temperature compensation table with based on these identified AC and DC for both TOSA and module parameters that influence its behavior. This solution will give a reasonable accuracy and will help reduce testing time, thus increasing manufacturing UPH.

1.4 Aim

The aim of this paper is to propose an ANN model to predict ER temperature compensation table that will help reduce testing time this increasing UPH with a reasonable network performance.

1.5 Objectives

This paper's research objectives are:

i. To determine the best parameters to produce ACBias based on relevant AC properties

ii. To develop and MLP ANN model utilizing the identified parameters in order to predict AC bias value which will be used in generating ER temperature compensation table.

1.6 Scope of the Research

The scope of this research are listed as follows:

i. Dataset

Data will be collected from two database. One is from Finisar's 100G/40G CGR4 QSFP28 optical transceiver module data from Ipoh site. Another data is Transceiver Optical Sub-Assembly data from Wuxi site.

ii. ANN model for predicting ER temperature compensation table

ANN model was designed using MatLab 2011a software. Multi-Layer Perceptron (MLP), and a network type which is feed forward model is the focus of this ANN.

1.7 Importance and Significance of the Research

In a manufacturing line, UPH is very important, it defines how well a manufacturing line performs. A high UPH shows that a manufacturing line output is high in a short period of time which is good. So, Finisar's manufacturing line tries its best to increase and improve its UPH. One way to improve UPH is by reducing manufacturing testing time to which this research will focus on. Through predicting temperature compensation table for extinction ratio of an optical transceiver module. Because whenever a value is predicted, then there will not be a need to test and subject the unit to test.

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