Non-linear Thermal Modeling Using Neural Networks

by

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Abstract

In this thesis a neural network-based modeling technique is proposed in order to perform non-linear thermal analysis of package models. A detailed thermal model, which physically represents the actual device geometry, is broken into smaller sub-models that are linked to a base-model through thermal ports. Sub-models exchange heat-flows with the base-model. These sub-models, with well defined thermal ports, are able to produce all the temperatures of interest in the detailed model.

A non-linear neural model is developed by training the neural network with a set of training data obtained from *Atar* simulation of the sub-model and the final quality of the trained model is evaluated by testing it with a set of testing data. The number of inputs (i.e., the number of ports of the sub-model) for the neural network model is determined by performing a linear simulation on the sub-model for different boundary conditions. The importance of ports of the sub-model is evaluated by determining the errors at different temperatures of interest of the sub-model with port configuration with respect to the temperatures of the detailed model. It has been shown that the neural network is capable of building the non-linear thermal model of packages with sufficient accuracy.

Finally, a detailed thermal model is represented with a number of sub-models. Temperatures at different points of interest of the sub-model are determined in an

iterative way by utilizing the Matlab/C code obtained from the neural network tool used in this thesis. It has been found that the model simulation becomes significantly faster when a detailed model is represented with a number of sub-models.

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List of Acronyms

3D	Three Dimensional
ANN	Artificial Neural Network
BC	Boundary Condition
BCI	Boundary Condition Independent
BGA	Ball Grid Array
BP	Back Propagation
CBGA	Ceramic Ball Grid Array
CG	Conjugate Gradient
FET	Field Effect Transistor
GaAs	Gallium Arsenide
GaN	Gallium Nitride
IC	Integrated Circuit
I/O	Input/Output
MLP	Multi Layer Perceptrons
PCB	Printed Circuit Board
RBF	Radial Basis Function
SiC	Silicon Carbide
SOM	Self Organizing Map
SOR	Successive Over Relaxation
TLM	Transmission Line Matrix
VLSI	Very Large Scale Integration

List of Symbols

ΔT	Temperature Rise
V	Voltage
P	Heat-flow (Power)
I	Current
Q	Heat/Charge
R	Resistance
G	Conductance
ρ	Resistivity
K	Thermal Conductivity
σ	Electrical Conductivity
C	Thermal Capacity/Capacitance
c_p	Specific Heat
ε	Permittivity
T_j	Junction Temperature
θ_{j-a}	Total Thermal Resistance
T_a	Ambient Temperature
q	Heat Transfer Rate
θ_{j-c}	Thermal Resistance of the Junction to Case
θ_{c-a}	Thermal Resistance of the Case/Leads to the Ambient Air
T_c	Case Temperature
$I^2 R$	Power Loss
$g(x, y, z)$	Volumetric Heat Generation
n_p	Number of Ports

T_p	Port Temperature
I_p	Port Heat-flow
F_p	Source Vector
A_{pp}	Transformation Matrix
$\Re$	Set of All Real Vectors
w	Weight
L	Total Number of Layers
l	Layer
N	Number of Neurons
x	Input Neuron
z	Hidden Neuron
n	Total Number of Input Neurons
i, j, k	Associated with Number of Inputs/Outputs
γ_s	Weighted Sum
$\sigma(\cdot)$	Neuron Activation Function
y	Output Neuron
m	Total Number of Output Neurons
d	Measured/Simulated Output
T_r	Training Data
$E(w)$	Training Error
p	Number of Optimization
η	Learning Rate
μ	Momentum Factor
N_w	Number of Iterations
g	Gradient
h	Conjugate Direction
H	Hessian Matrix
δ	Relative Testing Error

T_e	Test Data
M	Maximum Error
$C_{coeff.}$	Correlation Coefficient
α	Heat Flow

Chapter 1

Introduction

This chapter starts with an overview of thermal modeling, describes the motivations behind the research work carried out in this thesis and presents the thesis methodology. Finally, it outlines the organization of the thesis.

1.1 Background

The recent trend in IC technologies is to develop smaller devices with higher packaging density, faster speed and improved performance. Higher levels of IC integration and faster clock speeds result in higher power consumption. With the shrinkage of device dimensions, the complexities in chips increase. Consequently, faster switching speeds and greater on-chip functionality lead to larger heat generation and significant non-uniformities in on-chip heat flux of electronic devices.

The major part of the failures of integrated electronic components is temperature related. The failure rate of microelectronic devices approximately doubles for every 10°C increase in temperature [1]. As a result, hot spots due to power dissipation have become

a major long term reliability concern. For high temperatures and harsh environment applications, the most critical issues [2] for designing electronic packages for micro systems are: (1) Mitigation of thermal stress caused by the thermal expansion mismatches between the devices and various package elements including substrates (2) Thermal shock resistance brought about by thermal cycling during the services (3) Heat dissipation in order to keep the temperatures at safe operation levels.

With the development of smaller, lighter, faster as well as more functional electronic components, the reliability issue of these components becomes one of the major concerns in electronic packaging. Specifically, the performance and the reliability of electronic systems strongly depend on the junction temperature of the electronic components of the system. Hence, the determination of the component junction temperature is of utmost importance in thermal analysis of an electronic system.

Increased power dissipation and higher packaging density in modern electronic system require efficient and intelligent design and thermal management strategies to ensure the reliability of electronic products. To optimize long term reliability and performance, it has become essential to perform thermal and electro-thermal modeling and simulation prior to chip fabrication. Thermal management of electronic components plays an important role in all levels of packaging, i.e., from chip to package and system level. Currently, thermal modeling at system level is carried out for the analysis of parametric trends; but the predictive capabilities of these models are limited in most cases [3]. It is important to develop a model that is able to detect all the operating temperatures of

various components in order to properly design the device or circuit layout and optimize thermal characteristics. The method should be fast, accurate and able to predict all critical temperatures.

1.2 Motivation

A common approach for thermal modeling is to utilize numerical modeling based on finite difference or other numerical techniques. A physical model based on this approach should be able to represent all the temperatures of interest of the original detailed structure. A large thermal model consisting of a die, package and board could have more than 500,000 blocks. A number of issues [4] are involved in such a large thermal package simulation: (1) Very long simulation time for both steady-state and transient (2) Non-linear effects due to a temperature dependent thermal conductivity (3) The need to predict the multiple junction temperatures in multi-chip modules or detailed temperature distributions for some applications, such as, in optical devices (4) The need to optimize device layout/package geometries which requires many simulations. For these reasons, it is necessary to develop an efficient thermal model that can accurately predict multiple temperatures and represent the package in a detailed manner.

The use of *sub-models* or *macro-models* is a very useful approach for thermal analysis of linear models. A *detailed model* [5], which is a discretized version of the physical model, can be created by using a numerical simulator, such as, *Atar* [6 – 8]. This model of the component is then used in order to create a sub-model. The use of sub-model allows

replacement of the complex parts of a large detailed model with a simple mathematical relationship. In order to create a sub-model it is needed to extract this relationship from the detailed model. This sub-model – linked to a detailed numerical model called the *base-model* through thermal ports – exchanges heat-flows with the base-model. The extraction of a linear sub-model can be performed straightforwardly in a number of ways [4].

Non-linear thermal modeling using sub-models requires a more general approach. The main challenge in non-linear component-modeling is to find the non-linear relationship between the port temperatures and port heat-flows of the sub-model. Precise mathematical modeling of such system is a very difficult task. Consequently, there is a need for an efficient modeling technique that can accurately represent the non-linear thermal behavior of the original model. *Neural network*-based modeling, a powerful technique that is capable of representing any non-linear relationship, can be applied to build a non-linear model of such system. However, the application of neural networks in thermal modeling has been left mostly unexplored so far by the research community [9]. The objective of this thesis is to investigate the neural network-based thermal modeling of electronic packages and to evaluate the performance of such models using a modeling tool called *Neuromodeler*.

1.3 Thesis Methodology

As indicated in Section 1.2, the neural network modeling technique can be applied to perform a non-linear thermal analysis of electronic packages/components. In this thesis, the non-linear thermal analysis has been performed on three different thermal models as follows: (a) A Gallium Nitride (GaN) on SiC power package amplifier, (b) A Gallium Arsenide (GaAs) based power amplifier and (c) Ceramic-Ball-Grid-Array (CBGA) single-chip package. The steps followed in order to perform the non-linear thermal analysis have been:

1. Selection of the number of inputs for neural network modeling has been based on the linear simulation of the three above mentioned models using a thermal simulator called *Atar*.
2. Generation of data for training the neural network model. The data has been generated through non-linear simulation of *Atar*.
3. Development of a neural network model – using a modeling tool called *Neuromodeler* – through a process called *training* where the model learns the original input-output relationships. After the model is trained with a set of training data, it can become a fast and accurate model of the original problem.
4. Evaluation of the quality of the trained neural model through a process called *testing* using a set of data called *testing data*. In this thesis, the accuracy of the trained neural model has been evaluated by the *average percentage error* of the neural model output with respect to the test data.

5. Full simulation of a *mixed-model* comprised of a detailed base-model and neural-network based sub-models.

1.4 Electro-Thermal Analogy

A thermal system is found to be analogous to an electrical system if they have similar equations and boundary conditions. The equations that describe the behaviors of an electrical system can be transformed into the equations for the analogous thermal system by simply changing the variables. The analogy between thermal and electrical systems allows one to predict the thermal characteristics with widely known basic laws and methods for electrical simulation and modeling. Since *Atar* represents the final thermal model as a network of resistors and capacitors it is useful to know the thermal-electrical analogy for intuitive understanding. The thermal-electrical analogies are provided in Table 1.1.

Table 1.1: An Analogy between Thermal and Electrical Quantities

Thermal Quantities		Units	Electrical Quantities		Units
Temperature Rise	ΔT	K	Voltage	V	V
Heat-flow (Power)	P	W	Current	I	A
Heat	Q	J=W.s	Charge	Q	C=A.s
Thermal Resistance	R	K/W	Resistance	R	$\Omega=V/A$
Thermal Conductance	G	W/K	Conductance	G	$S=\Omega^{-1}$
Thermal Resistivity	ρ	K.m/W	Electrical Resistivity	ρ	$\Omega.m$
Thermal Conductivity	K	W/K.m	Electrical Conductivity	σ	S/m
Heat Capacity	C	J/K	Capacitance	C	F=C/V
Specific Heat	c_p	J/kg.K	Permittivity	ϵ	F/m

1.5 Organization of the Thesis

In this thesis, a non-linear thermal modeling based on neural network approach is presented. In this chapter, the problem domain of the thesis work has been described and the proposed approach has been outlined. The remaining part of the thesis is organized as follows:

- Chapter 2 provides a brief introduction of packaging along with various thermal issues in packaging. It also discusses simulation and modeling approaches involved in thermal packaging.
- Chapter 3 presents the basic concepts of the neural network-based modeling approach. It also discusses various well known neural network structures. Finally, it discusses the training algorithms as well as the testing of neural network models.
- Chapter 4 presents the linear simulations performed using *Atar* in order to determine the number of inputs for neural network modeling.
- In Chapter 5, a neural model is developed using *Neuromodeler* for each of the three models mentioned in Section 1.3. The qualities of the developed models are evaluated.
- In chapter 6, the use of neural network in thermal modeling is presented for mixed-models.
- In Chapter 7, conclusions and future research directions are stated.

Chapter 2

Thermal Issues in Packaging

This chapter starts with a brief introduction of electronic *packaging* and presents a review of *thermal issues* – one of the most important aspects of packaging. It also discusses the associated non-linear thermal equation. Finally, it provides a brief summary on *simulation and modeling* of thermal packaging.

2.1 Introduction to Packaging

With the rapid development of very large scale integration (VLSI) technologies, millions of electronic components with more functions and higher speeds are being fabricated on a single integrated circuit (IC) chip. As the circuit density on the chip increases, the speed of the tasks it performs also increases. To perform its functions, the IC chip communicates with other IC chips in a circuit through an input/output (I/O) system of interconnects. *Packaging* focuses on how these chips along with their embedded circuitry can be assembled cost effectively and with increased reliability.

The need for miniaturization, higher reliability and competitive pricing has pushed product design far beyond the limitations of the conventional technology and has necessitated the development of new packaging technologies in order to insure that the final product meets the severe operational environments, cost restrictions and reliability standards of the industry. *Packaging* of electronic systems, in general, refers to the placement and connection of many electronic and electromechanical components in an enclosure in order to protect the system from the hostile environment and provide easy access for routine maintenance [10]. Based on the science of establishing interconnections, packaging encompasses the group of chip carriers or modules, printed circuit cards and boards, and cabling and connectors that make up an electronic assembly [11]. Starting from a single chip, which has been fabricated on a silicon wafer; the packaging process involves different stages [10] as shown in Figure 2.1. These stages are discussed briefly in the subsequent discussion.

First Level of Interconnections: Chip is housed and connected electrically to the carrier, often called a module, through some small wires.

Second Level of Interconnections: Chip carriers are placed on the circuit board and connected together with wiring traces formed by photo-etching the circuit board.

Third level of Interconnections: Connectors on the circuit boards are then inserted into contacts on a back panel. This back panel carries higher level of connections to communicate from one circuit board to other. Finally, the entire array of circuit boards, back panel, power supplies and cables are housed in a cabinet.

Figure 2.1: A Schematic Illustration of Several Levels of Packaging Involved in an Electronic System [10]

Electronic packaging will play a critical role in the next generation of semiconductor technology. The packaging aspect of the design of an electronic system is extremely important because about one-half of the cost of a system is involved in packaging [10]. Packaging provides a variety of mechanical, thermal and electrical functions. The major goals [10 – 12] of the electronics packaging are:

- **Power Distribution:** To provide a mechanism for delivering power to the semiconductor circuits with a high degree of stability and free of electrical noise, which can arise when many digital circuits switch simultaneously.

- **Signal Distribution:** To carry electrical signals from one circuit to another, while maintaining fidelity of the signal even at the highest speeds at which the circuitry can operate.
- **Thermal Management:** To maintain internal product/system and device temperature by removing the excess heat generated by the circuits on the IC chip.
- **Protection:** In addition to carefully packing thousands of electronic components into a stylish and functional cabinet, packaging protects these components and the circuitry from hostile environments as well as from abusive handling.

The thermal aspects of packaging are discussed in more detail in the following section.

2.2 Thermal Packaging

The diverse applications of electronic products and the recent acceleration of packaging technology are creating new challenges to the thermal design. Placing more functions in a smaller package results in higher heat densities. Higher operating temperatures accelerate various failure mechanisms, such as, creep, corrosion, electro-migration etc. [11]. Large fluctuations or variations of temperature causes malfunction or even breakdown of the equipment. In order to protect the chip and to keep it running at its design temperature, the excess heat needs to be dissipated. Since the operating temperature of the chips markedly affects the reliability of the circuit board, system availability and serviceability

of electronic equipments, *heat management* plays one of the most important roles in electronic packaging.

Thermal management of electronic packaging is an all-inclusive method that involves the selection, analysis, testing, and verification of a cooling design in order to produce a reliable end product [13]. With the very large number of components used in a typical electronic system, it is necessary to minimize the *junction temperatures* (T_j) of the most critical of the components for enhancing the reliability and improving the availability of the system. Consequently, the goal of thermal management is to move the heat out of the junctions of power-dissipating devices while minimizing cost, noise and overall complexity and size of the heat-removing devices [14].

Thermal analysis of electronic system involves the prediction of the junction temperature of the integrated circuits. The point, at which the maximum temperature of a chip is reached, is considered as the junction temperature. The main purpose of thermal packaging is to create and maintain a temperature distribution with limited variations around a moderate level across the transistor junctions by placing the heat generating components in the proper location in a package and by measuring the heat that needs to be disposed to the exterior of the equipment. The trend to increase chip power dissipation has become a major concern for the circuit designers and places significant emphasis on thermal design considerations at all levels of electronic packaging, i.e., from the chip level to the system level [11].

The heat transfer characteristics of an IC package is usually specified in terms of its total thermal resistance θ_{j-a} ($^{\circ}\text{C}/\text{W}$), which refers to the temperature difference between the junction temperature T_j ($^{\circ}\text{C}$) of the electronic device and the ambient temperature T_a ($^{\circ}\text{C}$) of the air flowing over the chip carrier [10, 13]. The temperature difference is,

$$T_j - T_a = q\theta_{j-a} \quad (2.1)$$

θ_{j-a} is defined as,

$$\theta_{j-a} = \theta_{j-c} + \theta_{c-a} \quad (2.2)$$

where, θ_{j-c} ($^{\circ}\text{C}/\text{W}$) is the thermal resistance of the junction to case and θ_{c-a} ($^{\circ}\text{C}/\text{W}$) is the thermal resistance of the case/leads to the ambient air and can be expressed as,

$$\theta_{j-c} = \frac{T_j - T_c}{q} \quad (2.3)$$

$$\theta_{c-a} = \frac{T_c - T_a}{q} \quad (2.4)$$

where, T_c ($^{\circ}\text{C}$) is the case temperature and q (W/m^3) is the heat transfer rate per unit volume. The resistance θ_{j-c} is due to conduction from the chip to the package and it involves the detailed design of the chip carrier. The resistance θ_{c-a} is due to convection and formation of a boundary layer between the case and its leads and the air.

2.3 Thermal Equation for Conduction

Heat is generated in electronic devices primarily by I^2R losses and must be dissipated in order to avoid excessive temperature that can impair the reliability of the system. The amount of heat generated varies from a few milliwatts (for example, in a wristwatch) to 10 kW or more (for example, in a large mainframe computer) depending on the size and complexity of the system. The design for dissipating the heat generated depends to a significant degree on the type of the product, the environment, the accessibility of a coolant, the reliability and the system availability requirements and also the cost involved in providing an adequate cooling system.

Heat is transferred from the component (source) to the environment (sink) by three basic mechanisms, which include conduction, convection and radiation. This thesis is focused only towards *conduction* which is associated with 1st and 2nd level of packaging.

Conduction is the most important heat transfer mechanism at the chip and package level. Conduction is due to the energy exchange of rapidly vibrating molecules in a hotter region to less rapidly vibrating molecules in a cooler region. Conduction is usually associated with solids but it may also occur in fluids (liquids and gases) over very short distances. The heat-flow from the junction of a chip in an IC package to its case is a common example of conduction [13].

The following partial differential equation [15] needs to be solved in order to solve the conductive heat-flow in an IC or package structure.

$$\nabla(K(T)\nabla T) + g(x, y, z) = 0 \quad (2.5)$$

where, $K(T)$ (W/m.K) is the temperature dependent thermal conductivity and $g(x, y, z)$ (W) is the volumetric heat generation. This is a steady state equation of heat conduction and allows calculating the temperature distribution in a structure containing heat sources having known boundary conditions.

For Si and with a temperature rise of $\Delta T < 100^\circ\text{C}$, $K \sim K_{300K}$, i.e., the Equation (2.5) is essentially linear. However, for III-V materials and a temperature rise of $\Delta T > 75^\circ\text{C}$, the temperature dependent thermal conductivity makes the Equation (2.5) non-linear. This temperature dependant nature of $K(T)$ is an important issue for power amplifiers and optical modules. This thesis is mainly focused towards the non-linear thermal behavior of an electronic package.

Due to the complex geometries and non-linear nature of the heat conduction equation in (2.5), it is very difficult to analytically solve the equation. To obtain solution for realistic packages, an appropriate discretized 3D model must be built in order to produce a numerical solution of the equation. The thermal simulator *Atar* described in the subsequent section of this thesis can be used to solve this non-linear equation.

2.4 Package Simulation and Modeling

Packaging technology increases the performance of electronic systems and subsystems while reducing their size. The thermal performance of packaging is typically predicted by two methods,

- Package modeling using simplified models of the physical heat-flow through geometry. These models are generally linear and produce an approximate junction temperature.
- Package simulation using a numerical thermal simulator. Simulation involves a detailed numerical simulation incorporating complex geometry and possibly non-linear effects. Typical methods are finite elements and finite difference. Simplified package models are often derived from simulations [5].

In the subsequent sections, a numerical tool for package simulation called *Atar* and the use of sub-models in thermal packaging is discussed. Finally, a neural network-based modeling tool called *Neuromodeler* used in this thesis is discussed.

2.4.1 Thermal Simulator – *Atar*

A common approach of simulation is to write computer codes that provide numerical solutions to the specified problems with complex geometries arising in electronic packaging. *Atar* [6 – 8] is a thermal simulator tool based on this approach. This tool was developed by the modeling group at Carleton University and has been used in this thesis for simulation purpose. It is a three-dimensional (3D) thermal simulation tool for semiconductor integrated devices, packages and assemblies. The simulation tool uses a technology description and layout information in order to automatically generate a full 3D physical model, complete with discretization, and then solves for the temperature distribution. The simulator automatically produces an accurate 3D model of the device from layout information which is appropriately meshed for solving the non-linear thermal diffusion equation that describes the heat-flow. A 3D model represents both the substrate of the device/package and any metallization that is present. A 3D quad tree mesh is created that produces a fine mesh at the heat generation region of the device, but still uses a moderate number of temperature nodes for the entire device. From this model, a network of thermal resistors and capacitors are extracted that mathematically represents the model which can be solved to obtain the temperature distribution. It is worthwhile to mention that for a non-linear model, the thermal resistors are temperature dependent.

Atar offers two steady state internal solvers. A direct solver sets up a global sparse array and solves the linear set of equations representing the thermal resistor network. The second solver uses a Successive Over Relaxation (SOR) technique of the nodal

temperature equations and is particularly useful for large or non-linear problems with temperature dependent material properties or boundary conditions (BCs).

Atar also incorporates a transient solver based on a transmission line matrix (TLM) implementation using a physical extraction of a resistance and capacitance network. The formulation allows for temperature dependent material parameters and a non-uniform time stepping.

Atar uses a hierarchical model building technique. The hierarchical model building technique is based on the idea of *component* and *sub-models*. The next section provides a discussion of the use of sub-models in thermal packaging.

2.4.2 Use of Sub-model in Thermal Modeling

As mentioned in Chapter 1, number of issues are involved in a large thermal package simulation, such as, very long simulation time for both steady-state and transient, non-linear effects due to a temperature dependent thermal conductivity, the need for prediction of the multiple junction temperatures in multi-chip modules or detailed temperature distributions for some applications, such as, in optical devices and also the need for optimizing the device layout/package geometries which requires many simulations. For these reasons, it is essential to develop an efficient thermal model to be able to accurately predict multiple temperatures and represent the package in a detailed manner.

The approach taken in *Atar* to solve this problem is to break the original model into smaller models that are then “linked” together. These smaller models are originally fully detailed *Atar* models which are referred as either a *base-model* or a *component-model*. The base-model is typically the largest scale structure in the simulation, for example, the PC board. A component-model is a well defined part of the simulation, such as, a package or chip. Often components are repeated within a model. *Atar* allows the linking of base-model and component-models to form a complete hierarchical simulation. For example, linking four packages to a board. However, simply linking together of all the fully detailed models does not make simulation times smaller as the number of elements in the model is the same as for single model of the entire structure; it only facilitates the building process. Figure 2.2 shows how sub-model is linked to a base-model of a mixed-model.

To reduce simulation time the component-models must be replaced by a mathematically equivalent model which eliminates the need to incorporate the component-model. This mathematical representation of a component-model is referred as a *sub-model*. *Sub-models*, which are linked to a base-model through thermal ports, exchange heat-flows with the base-model. Well defined multiple ports must be utilized for an accurate representation of the thermal behavior of a component-model. By linking sub-models with a base-model a *mixed-model* is formed. A thermal simulation of such a model involves a *detailed* numerical model, the base-model linked to sub-models through thermal ports where the linking size of a sub-model is $n_p \times n_p$, where n_p denotes the

number of ports. The accuracy and determination of the internal temperatures of the sub-model depend on the geometry of the ports. The ports are characterized by two parameters: a port temperature $\vec{T}_p$ and port heat-flow $\vec{I}_p$ that are analogous to port voltage and port current respectively in an interconnected electrical sub-network.

For a linear model, the thermal equations representing the component-model can be generated by *Atar*. If the BCs and thermal ports of the component-model are explicitly described, the linear relationship between the port heat-flows and temperatures can be characterized by Equation (2.6).

$$\vec{I}_p = \vec{F}_p + G_p \vec{T}_p \quad (2.6)$$

where, $\vec{F}_p \in \mathbb{R}^{n_p \times 1}$ is the source vector representing internal power generation and applied boundary conditions, $G_p \in \mathbb{R}^{n_p \times n_p}$ is the discretized thermal conductance matrix, $\vec{T}_p \in \mathbb{R}^{n_p \times 1}$ is the unknown vector of port temperatures in the system and p denotes the port. *Atar* allows for the connection and *linking* of a sub-model described by (2.6) to a detailed base-model and then solution of the mixed-model. The solution will produce all the internal temperatures of the base-model, the port temperatures and the internal temperatures of interest for the component-model. In the case where the model is linear, as in Equation (2.6), *model reduction* techniques can be used to capture the behavior of a large model by creating a small, fast reduced sub-model which is parameterized for external BCs. This is shown schematically in Figure 2.2 (b).

Figure 2.2 (a): Schematic Representation of a Mixed-Model Including a Two-port Sub-model Attached to a Base-Model (PCB) [4]

Figure 2.2 (b): Schematic Representation of Relationship between Components in a Mixed-model Using a Linear Sub-model [4]

The sub-modeling approach described above is very useful for linear thermal models; however, non-linear models (where K is a function of T) require a more general approach. For the non-linear case, the port heat-flow can be represented by Equation (2.7).

$$\vec{I}_p = f(\vec{T}_p) \quad (2.7)$$

where, f is a non-linear function. The first problem with a non-linear component is to find the non-linear relationship between the port temperatures and port heat-flows. The second issue that arises is that the mixed-model is now non-linear and it is more difficult to solve such system. However, as we shall see, *neural network* technique can be applied to build a non-linear model of such system and the solution of the mixed-model can then be done by iteration. In the next section, a neural network-based modeling tool, called *Neuromodeler*, which is used in this thesis, is described.

2.4.3 Thermal Modeling Tool – *Neuromodeler*

In this thesis, a neural network-based modeling tool, *Neuromodeler* [16], is used to analyze the non-linear behavior of thermal models. *Neuromodeler*, developed in Carleton University, is a unique software tool. It allows quick development of neural network models for active and passive components at both device and circuit-levels for linear or non-linear simulations. Models developed by *Neuromodeler* are much faster than original

detailed models, more accurate and flexible than empirical models. The neural networks technique used in this tool are discussed in detail in Chapter 3.

The inputs for *Neuromodeler* in this thesis are the port temperatures (T_p 's), input power (P) and boundary conditions (BC 's) applied to the sub-model. Outputs are the port heat-flows (I_p 's) and temperatures of interest (T_j 's). A thermal model is developed through a process called *training*. The performance of this model is evaluated by testing it with a set of *testing data*. The MATLAB/C code obtained from the *Neuromodeler* is used to link the sub-model with the base-model.

2.5 Summary

In this chapter, a review of packaging with an emphasis on the *thermal packaging* has been presented. A brief discussion on *simulation and modeling* has been provided. In the next chapter, a review on the *neural network*-based modeling approach that has been used in this thesis is presented.

Chapter 3

Neural Networks

This chapter presents the basic concepts on neural network-based modeling approach where the model can be developed by learning from the available data obtained from the original system. Some widely-used neural network structures are discussed. Finally, a brief discussion on the training algorithms and various quality measures involved in neural network testing are provided.

3.1 Introduction to Neural Networks

Neural networks, also called artificial neural networks (ANN), have been widely applied to various fields because of their ability to solve cumbersome or intractable problems by learning directly from data. *Neural network* is an information processing system inspired by the ability of the human brain to learn from observations and to generalize by abstraction [17]. In other words, as in [18], it is a massively parallel distributed processor made up of simple processing units which has a natural propensity of storing experiential knowledge and making it available for use. Neural networks, being able to learn and generalize from data even when component formulas are not available, allow reuse of the

same modeling technology for both linear and non-linear problems and at both device and circuit levels.

ANN is considered to be a powerful technique for modeling general input-output relationships. Models are provided with sufficient training data from which it learns the underlying input/output mapping. The main characteristics [17, 18] of ANN are:

Input-Output Mapping: Neural networks are capable of learning the non-linear behaviors directly from measured or simulated input-output data of the original circuit; consequently, manual effort of developing equivalent-circuit topology can be avoided [19]. Neural networks do not require any prior knowledge of input-output mapping for modeling and can easily infer the unknown input-output relationships from the training data provided to the network. As a result, the fitted function can be accurately represented by an ANN even if it is not explicitly defined.

Generalization: It is the ability of a network to estimate the output accurately when presented with the input that is never used during training. Neural networks have good generalization capability since they can respond correctly to new data that has not been used for model development.

Non-linearity: Neural networks are able to model highly non-linear as well as linear input-output mappings. They are capable of forming an arbitrarily close approximation to any continuous non-linear mapping [20].

3.2 Neural Network Structures

A general theory of information processing based on networks of binary switching or decision elements, which are somewhat euphemistically called *neurons* was proposed by McCulloch and Pitts [21]. A neural network model, also called connectionist network, consists of at least two physical components: (1) the processing elements, called *neurons* (2) connections between the neurons, known as the *links*. Every link in the network is associated with a weight parameter $\vec{w}$ that is adjusted during training process so that the *error* between the neural model outputs and the original problem outputs is minimized. Since the links and their weights determine the behavior of a model, they are considered as the important parameters of any model.

Neurons, receiving stimuli from outside the network (i.e., not from neurons of the network), are called *input neurons* while the neurons having no link leading away from them and whose outputs are used externally are called *output neurons*. *Hidden neurons* are the neurons that receive stimuli from other neurons and whose output is a stimulus for other neurons in the network.

To determine the appropriate number of hidden neurons required for a modeling task is still a topic of ongoing research. Depending on the degree of non-linearity and the dimensionality of the original problem, an appropriate number of hidden neurons in a network is chosen. For example, highly non-linear problems need more hidden neurons while smoother problem needs fewer neurons [17, 22]. Since the number of hidden

neurons gives sufficient freedom to the network to accurately learn the problem behavior and to capture the problem non-linearity, too many or insufficient number of hidden neurons may cause over-learning or under-learning respectively.

Neurons are connected to one another in different ways. After receiving stimulus from the neighboring neurons, each neuron (except the input neurons) processes the information and produces an output. Information can be processed by a neuron in various ways. The manner in which the output is computed from the input and the definition of the weight parameter $\vec{w}$ determine the structure of neural network. Different neural network structures are used depending on the application. Multi Layer Perceptrons (MLP), Radial Basis Functions (RBF) Networks, Wavelet Neural Networks, Recurrent Neural Networks, Knowledge Based Neural Networks are some examples of different neural network structures. Neural network structure may differ in accuracy and efficiency. In fact, selection of right type of structure appropriate for a particular application may give better accuracy while having less training data. The significant features [17] of neural network structures are:

- Neural networks are distributed models by nature. No single neuron is capable of producing the overall input-output relationship; the combination of many neurons can produce this relationship. Each neuron is a simple processing element having a switching activation function. This rich combination of the neuron switching states responding to different values of external stimuli enables the network to represent a non-linear input-output mapping.

- Neural networks can be trained to represent any given problem behavior because of their powerful learning capability. Neural networks with different sets of weighted connections are capable of representing a diverse range of input-output mapping problems by capturing/encoding the problem information from the raw training data.

In the subsequent sections, some widely-used neural network structures, with an emphasis on MLP which has been used in this thesis, are discussed.

3.2.1 Multi Layer Perceptrons

An extensive study on a specific type of neural network, called a *perceptron*, was conducted by Rosenblatt and his collaborators [23]. The flow of information in this neural network structure is strictly directional – from input neurons to output neurons. This idea led to a basic type of neural networks, called *feed-forward* networks. Feed-forward networks are capable of approximating generic classes of functions, including continuous and integrable functions [17, 24].

The *Multi Layer Perceptrons (MLP)* structure, belonging to feed-forward, is the most popular type of neural network since this structure and its training are well-established and the model has good generalization capability. It is considered to be the simplest structure capable of representing any Boolean function and of approximating more general functions to arbitrary precision [25]. An MLP structure consists of a set of sensory units (source nodes) that constitute the input layer (the first layer of the network),

one or more hidden layers of computation nodes, and an output layer (the last layer of the network) of computation nodes as shown in Figure 3.1. Suppose the total number of layers is L . The 1^{st} layer is the input layer, the L^{th} layer is the output layer and layers 2 to $(L-1)$ are hidden layers. Let the number of neurons in l^{th} layer be $N_l, l = 1, 2, \dots, L$.

Figure 3.1: Multi Layer Perceptrons (MLP) Structure [17]

Let w_{ij}^l represents the weight of the link between j^{th} neuron of $(l-1)^{th}$ layer and i^{th} neuron of the l^{th} layer, $1 \leq j \leq N_{l-1}, 1 \leq i \leq N_l$. Let x_i represents the i^{th} external neuron to the MLP, and z_i^l be the output of i^{th} neuron of l^{th} layer. Let w_{i0}^l , an extra weight parameter for each neuron, represents the bias for i^{th} neuron of l^{th} layer. As such, $\vec{w}$ of MLP includes $w_{ij}^l, j = 0, 1, \dots, N_{l-1}, i = 1, 2, \dots, N_l, l = 2, 3, \dots, L$, that is,

$$\vec{w} = [w_{10}^2 w_{11}^2 w_{12}^2 \dots, w_{N_L}^L N_{L-1}]^T \quad (3.1)$$

In a neural network, each neuron – with the exception of input neurons – receives and processes stimuli (inputs) from other neurons and the processed information is available at the output end of the neuron. In order to understand how each neuron in an MLP processes the information, let x_i represent the i^{th} external input to the MLP, and z_i^l be the output of the i^{th} neuron of l^{th} layer. A neuron of the l^{th} layer receives stimuli from the neurons of $(l-1)^{th}$ layer, i.e., $z_1^{l-1}, z_2^{l-1}, \dots, z_{N_{l-1}}^{l-1}$. Each input is first multiplied by the corresponding weight parameter and the resulting products are then added to produce a weighted sum γ_s . This weighted sum is passed through a neuron activation function $\sigma(\cdot)$ in order to produce the final output z_i^l . This final output z_i^l becomes the stimulus for neuron in the next layer. The input neurons simply relay the external stimuli to the hidden layer neurons; i.e., the input neuron activation function is a relay function, $z_i^l = x_i, i = 1, 2, \dots, n$ and $n = N_1$.

The activation function used in neural network can be logistic function, such as, *sigmoid* or simple linear functions that compute the weighted sum of the stimuli. In order to model continuous electrical parameters, linear activation functions are more suitable for output neurons. The use of linear activation functions in the output neurons helps to improve the numerical conditioning of the neural network training process. The linear activation function is defined as,

$$\sigma(\gamma_s) = \gamma_s = \sum_{j=0}^{N_{l-1}} w_{ij}^L z_j^{L-1} \quad (3.2)$$

where, w_{ij}^L represents the weight of the link between j^{th} neuron of the $(L-1)^{th}$ layer and the i^{th} neuron of the L^{th} layer.

The most commonly used hidden neuron activation function is the sigmoid function given by,

$$\sigma(\gamma_s) = \frac{1}{1 + e^{-\gamma_s}} \quad (3.3)$$

where, $\sigma(\gamma_s) \rightarrow 1$ as $\gamma_s \rightarrow +\infty$ and $\sigma(\gamma_s) \rightarrow 0$ as $\gamma_s \rightarrow -\infty$

Figure 3.2: Information Processing by i^{th} Neuron of l^{th} layer [17]

Other possible hidden neuron activation functions are the arc-tangent function given by,

$$\sigma(\gamma_s) = \frac{2}{\pi} \arctan(\gamma_s) \quad (3.4)$$

and the hyperbolic tangent function given by,

$$\sigma(\gamma_s) = \frac{e^{\gamma_s} - e^{-\gamma_s}}{e^{\gamma_s} + e^{-\gamma_s}} \quad (3.5)$$

All of these logistic functions [17] mentioned above are bounded, continuous, monotonic and continuously differentiable.

Let, the inputs $\vec{x} = [x_1 x_2 \dots x_n]^T$ and the weights $\vec{w}$ are used to compute the outputs $\vec{y} = [y_1 y_2 \dots y_m]^T$ from an MLP neural network. In the feed-forward process, such as, in MLP, the external inputs are first fed to the input neurons (1^{st} layer). Then the outputs from the input neurons are fed to the hidden neurons of the 2^{nd} layer, and so on. Finally, the outputs of the $(L-1)^{th}$ layer are fed to the output neurons of L^{th} layer. The computation is represented as,

$$z_i^l = x_i, i = 1, 2, \dots, N_1, \text{ and } n = N_1 \quad (3.6)$$

$$z_i^l = \sigma \left(\sum_{j=0}^{N_{l-1}} w_{ij}^l z_j^{l-1} \right), i = 1, 2, \dots, N_l, l = 2, 3, \dots, L \quad (3.7)$$

The outputs of the neural network extracted from the output neurons are as follows,

$$y_i = z_i^L, i = 1, 2, \dots, N_L, m = N_L \quad (3.8)$$

The weights $\vec{w}$ are fixed during a feed-forward computation and these weights are determined through the training process.

According to the universal approximation theorem, there exists a three-layer MLP that approximates virtually any arbitrary non-linear, continuous, multi dimensional function with any desired accuracy [17]. MLP networks can construct global approximation to non-linear input-output mapping. Consequently, they are capable of generalizing in those regions of the input space where little or no training data is available. Moreover, neural networks with one hidden layer are necessary and sufficient for arbitrarily non-linear function approximation. In practice, neural networks with one or two hidden layers are more commonly used. The performance of a neural network can be evaluated in terms of generalization capability and mapping capability [26]. In the function approximation or regression area, generalization capability is a major concern. In such applications, three-layer perceptrons are usually preferred because of having fewer hidden neurons in the resulting network [27]. In other type of applications, where better mapping capability is necessary, four-layer perceptrons might be utilized [26]. In this thesis, both three-layer and four-layer perceptrons structures have been used for thermal package modeling.

3.2.2 Radial Basis Function Networks

Feed-forward neural networks with an input layer, an output layer and a single hidden layer that use radial basis activation functions for hidden neurons are called *Radial Basis Function (RBF)* networks [17]. Gaussian and multi-quadratic activation functions are more commonly used in RBF. RBF is suitable for problems with smaller number of inputs.

3.2.3 Wavelet Neural Networks

Wavelet neural network construction method is developed by using the theoretical features of the wavelet transform [17]. This method helps to determine the neural network parameters and the number of hidden neurons during training. Wavelet networks use wavelet function as hidden neuron activation function.

3.2.4 Recurrent Neural Networks

Recurrent neural network structure, having at least one feed-back loop, allows modeling the time-domain behavior of a dynamic system where the outputs of the system depend not only on the present inputs, but also on the history of the system states and inputs [17].

3.3 Training of Neural Networks

Development of a neural network model for a device – circuit is possible by learning and abstracting from measured – simulated data through a process called *training* [28]. It learns the original input-output relationship through training and does not represent any device – circuit behavior unless it is trained with corresponding device – circuit data. The purpose of *training*, which is the most time-consuming step in neural network model development, is to determine neural network integral weights $\vec{w}$ such that the neural model output best matches the training data. The neural network becomes a fast and accurate model of the original problem it has learnt after it is trained with sufficient data.

Training algorithm, which can be viewed as an optimization process for finding values of weights associated with various neurons, is an integral part of neural network model development. An appropriate structure may still fail to give a better model, unless trained by a suitable algorithm [28]. A good training algorithm is likely to shorten the training time and would help achieving a better accuracy. Various well known optimization techniques that are used to train neural network structures are: Back Propagation, Conjugate Gradient, Quasi-Newton, Levenberg-Marquardt, Gauss-Newton, Genetic Algorithms and Simulated Annealing.

The most challenging task in neural model development is to find an optimal set of weight parameter $\vec{w}$, so that the model output $\vec{y}(\vec{x}, \vec{w})$ closely approximates the original

problem behavior. This is achieved through the training process (optimization in $\vec{w}$ – space) with a given set of training data. A good collection of well-distributed, sufficient and accurately measured – simulated training data is the basic requirement to obtain an accurate model [28]. The training data is denoted by the input-output sample pairs $\{(x_k, d_k), k \in T_r\}$, where d_k is the measured/simulated output for $\vec{y}$ for the input x_k , and T_r is the index set of training data. The measured/simulated outputs are related by $d_k = f(x_k)$. The training error $E(\vec{w})$ is defined as [17],

$$E(\vec{w}) = \sum_{k \in T_r} E_k(\vec{w}) \quad (3.9)$$

where, $E_k(\vec{w})$ is the error between neural network prediction and the k^{th} training sample given by,

$$E_k(\vec{w}) = \frac{1}{p} \sum_{j=1}^m \left| y_j(x_k, \vec{w}) - d_{jk} \right|^p \quad (3.10)$$

where, m is the dimension of the output $\vec{y}$,

p represents least p^{th} optimization,

d_{jk} is the j^{th} element of d_k ,

and $y_j(x_k, \vec{w})$ is the j^{th} output of the neural network for input sample

x_k .

The primary objective of the training process is to determine the weight parameters $\vec{w}$ such that the error $E(\vec{w})$ is minimized.

The normalized training error [17] is defined as,

$$E_{T_r}(\vec{w}) = \left[\frac{1}{size(T_r).m} \sum_{k \in T_r} \sum_{j=1}^m \left| \frac{y_j(x_k, \vec{w}) - d_{jk}}{d_{\max,j} - d_{\min,j}} \right|^p \right]^{\frac{1}{p}} \quad (3.11)$$

where, $d_{\max,j}$ and $d_{\min,j}$ are the maximum and minimum values of the j^{th} element of all vectors of d_k , $k \in T_r$.

The training process can be classified into two groups, namely, *supervised* training and *unsupervised* training. The training, in which both the input data $\begin{pmatrix} \vec{x} \end{pmatrix}$ and output data $\begin{pmatrix} \vec{y} \end{pmatrix}$ are used to train the neural network, for example, in MLP training, is called supervised training. On the other hand, in unsupervised training, either the input data $\begin{pmatrix} \vec{x} \end{pmatrix}$ or the output data $\begin{pmatrix} \vec{y} \end{pmatrix}$ is used for training, as in *self-organizing map* (SOM) training.

3.3.1 Back Propagation

Rumelhart, Hinton and Williams [29] proposed a systematic neural network training approach and one of the significant contributions of their work is the error *Back Propagation (BP)* algorithm. BP, belonging to supervised learning, is considered as a computationally efficient method for the training of Multi Layer Perceptrons [18].

The first step of training is to initialize the weight parameter $\vec{w}$ by using small random values. The weight parameter $\vec{w}$ is updated during training along the negative direction of the gradient of the training error E , as $\vec{w} = \vec{w} - \eta \left(\frac{\partial E}{\partial \vec{w}} \right)$ until E becomes small enough.

Here, the parameter η is called the learning rate. In the case where just one training sample is used at a time to update $\vec{w}$, a per-sample error function E_k [17] given by,

$$E_k = \frac{1}{2} \sum_{j=1}^m \left\{ y_j \left(x_k, \vec{w} \right) - d_{jk} \right\}^2 \quad (3.12)$$

is used and $\vec{w}$ is updated as $\vec{w} = \vec{w} - \eta \left(\frac{\partial E_k}{\partial \vec{w}} \right)$.

Back propagation is a stochastic algorithm based upon the steepest descent principle [30]. In this case, the weights of the neural network are updated along the negative gradient direction in the weight space. The updated equations are given by,

$$\Delta \vec{w}_{now} = \vec{w}_{next} - \vec{w}_{now} = -\eta \frac{\partial E_k(\vec{w})}{\partial \vec{w}} \bigg|_{\vec{w}=\vec{w}_{now}} \quad (3.13)$$

or

$$\Delta \vec{w}_{now} = \vec{w}_{next} - \vec{w}_{now} = -\eta \frac{\partial E_T(\vec{w})}{\partial \vec{w}} \bigg|_{\vec{w}=\vec{w}_{now}} \quad (3.14)$$

where, the learning rate η controls the step size of weight update. Equation (3.13) is called the *update sample-by-sample*, in which the weights are updated after each training sample is presented to the network while Equation (3.14) is called *batch mode update*, in which the weights are updated after all training samples are presented to the network.

The basic back propagation algorithm suffers from slower convergence and possible weight oscillation [17] which may cause the change of $\frac{\partial E_T}{\partial \vec{w}}$ between samples. In order

to solve this situation, η is kept small and a momentum term is added. The addition of a momentum term to the Equations (3.13) and (3.14), as proposed by [29], results in a significant improvement to the basic back propagation by reducing the weight oscillation. The updated formulae with the momentum are shown in Equations (3.15) and (3.16).

$$\Delta \vec{w}_{now} = -\eta \frac{\partial E_k(\vec{w})}{\partial \vec{w}} \bigg|_{\vec{w}=\vec{w}_{now}} + \mu \Delta \vec{w}_{old} = -\eta \frac{\partial E_k(\vec{w})}{\partial \vec{w}} \bigg|_{\vec{w}=\vec{w}_{now}} + \mu(\vec{w}_{now} - \vec{w}_{old}) \quad (3.15)$$

$$\Delta \vec{w}_{now} = -\eta \left. \frac{\partial E_{T_r}(\vec{w})}{\partial \vec{w}} \right|_{\vec{w}=\vec{w}_{now}} + \mu \Delta \vec{w}_{old} = -\eta \left. \frac{\partial E_{T_r}(\vec{w})}{\partial \vec{w}} \right|_{\vec{w}=\vec{w}_{now}} + \mu(\vec{w}_{now} - \vec{w}_{old}) \quad (3.16)$$

where, μ is the momentum factor that controls the influence of the previous weight update direction on the current weight update, and $\vec{w}_{old}$ is the previous value of $\vec{w}$. This technique is also known as the *generalized delta-rule* [18].

The efficiency of training by back propagation can be improved by using adaptation schemes that allow the learning rate and the momentum factor to be adaptive during learning, such as, adaptation according to training errors [28].

3.3.2 Conjugate Gradient

Conjugate Gradient methods are very effective for training large neural networks since they scale well with the neural network size. These methods are originally derived from quadratic minimization. In this case, the minimum of the objective function E_{T_r} can be

effectively found within N_w iterations. Given the initial gradient $\vec{g}_{initial} = \left. \frac{\partial E_{T_r}}{\partial \vec{w}} \right|_{\vec{w}=\vec{w}_{initial}}$,

and direction vector $\vec{h}_{initial} = -\vec{g}_{initial}$, the conjugate gradient method recursively constructs two vector sequences [31],

$$\vec{g}_{next} = \vec{h}_{now} + \lambda_{now} H \vec{h}_{now} \quad (3.17)$$

$$\vec{h}_{next} = -\vec{g}_{next} + \gamma_{now} \vec{h}_{now} \quad (3.18)$$

$$\lambda_{now} = \frac{\vec{g}_{now}^T \vec{g}_{now}}{\vec{h}_{now}^T H \vec{h}_{now}} \quad (3.19)$$

$$\gamma_{now} = \frac{\vec{g}_{next}^T \vec{g}_{next}}{\vec{g}_{now}^T \vec{g}_{now}} \quad (3.20)$$

or,

$$\gamma_{now} = \frac{(\vec{g}_{next} - \vec{g}_{now})^T \vec{g}_{next}}{\vec{g}_{now}^T \vec{g}_{now}} \quad (3.21)$$

where, $\vec{h}$ is the conjugate direction, H is the Hessian matrix of the objective function E_T , and λ, γ are two scalars. Here, Equation (3.20) is called the Fletcher-Reeves formula [32] and Equation (3.21) is called the Polak-Ribiere formula [33]. In order to avoid the Hessian matrix computation for determining the conjugate direction, one needs to proceed from w_{now} , along the direction $\vec{h}_{now}$ to the local minimum of E_T at w_{next} through

line minimization, and then set $\vec{g}_{next} = \left. \frac{\partial E_T}{\partial w} \right|_{w=w_{next}}$. This $\vec{g}_{next}$ can be used as the vector of

Equation (3.17). In this way, Equation (3.19) is no longer needed and the descent direction runs along the conjugate direction, which can be accumulated without matrix computations.

3.4 Quality Evaluation of Neural Networks

The final quality, including the generalization capability of a trained neural model is tested with an independent set of data, called *test data*. The accuracy of the trained neural model is measured by the *average percentage error* of the neural model output versus test data. Different factors [17] that indicate the quality of the neural model are discussed briefly in the subsequent discussion.

The relative error for the j^{th} output of neural model on k^{th} data sample is defined by,

$$\delta_{kj} = \frac{y_j(x_k, \vec{w}) - d_{jk}}{d_{\max,j} - d_{\min,j}}, \quad j = 1, \dots, m \text{ and } k \in T_e \quad (3.22)$$

where, T_e is the index set of test data.

A quality measure based on the p^{th} – norm measure is then defined as,

$$M_p = \left[\sum_{k \in T_e} \sum_{j=1}^m |\delta_{kj}|^p \right]^{\frac{1}{p}} \quad (3.23)$$

When $p = 1$, the average test error can be directly calculated from M_1 as,

$$\text{Average Test Error} = \frac{M_1}{\text{Size}(T_e)m} = |\bar{\delta}| \quad (3.24)$$

where, $|\bar{\delta}|$ is the mean value of absolute error $|\delta_{kj}|$ for all k and j .

When $p = \infty$, the p^{th} – norm measure is the maximum test error, also known as worst-case error among the entire test data and all model outputs, that is,

$$Worst-case Error = M_{\infty} = \max_{k \in T_e} \max_{j=1}^m |\delta_{kj}| \quad (3.25)$$

The error mean $\bar{\delta}$ can be defined as,

$$Mean(\delta) = \frac{1}{Size(T_e)m} \sum_{j=1}^m \sum_{k \in T_e} \delta_{kj} = \bar{\delta} \quad (3.26)$$

The histogram of absolute error $|\delta|$ can be a useful graphical representation of the quality of a neural model.

The correlation between neural model and test data, called the correlation coefficient, is defined as,

$$C_{coeff.} = \frac{\sum_{j=1}^m \sum_{k \in T_e} (y_j(x_k, \vec{w}) - \overline{y(x, \vec{w})})(d_{jk} - \overline{d_{jk}})}{\left(\left[\sum_{j=1}^m \sum_{k \in T_e} (y_j(x_k, \vec{w}) - \overline{y(x, \vec{w})})^2 \right] \left[\sum_{j=1}^m \sum_{k \in T_e} (d_{jk} - \overline{d_{jk}})^2 \right] \right)^{1/2}} \quad (3.27)$$

where, $\overline{y(x, \vec{w})}$ represents the mean of the neural network outputs given by,

$$\overline{y(x, \vec{w})} = \frac{1}{Size(T_e).m} \sum_{j=1}^m \sum_{k \in T_e} y_j(x_k, \vec{w}) \quad (3.28)$$

and $\overline{d_{jk}}$ represents the mean of the measured/simulated outputs in the test data given by,

$$\overline{d_{jk}} = \frac{1}{Size(T_e).m} \sum_{j=1}^m \sum_{k \in T_e} d_{jk} \quad (3.29)$$

3.5 Summary

In this chapter, an overview on the neural network-based system modeling technique has been presented. Different neural network structures and training algorithms have been discussed. It appears that in order to solve difficult and diverse problems, *Multi Layer Perceptrons (MLP)* structures can be utilized by training them in a supervised manner with the two widely used algorithms: *Back Propagation (BP)* and *Conjugate Gradient (CG)*. Consequently, these approaches have been adopted in this thesis to perform thermal analysis on electronic packaging as discussed in the subsequent chapters.

Chapter 4

Sub-model Definition

This chapter begins with a discussion on the geometric definition of *sub-models* for use in hierarchical modeling. It then presents the results used for the definition of sub-model of three package models using linear *Atar* simulations. These simulations are performed in order to decide the number of inputs, i.e., the appropriate port configuration for neural network modeling.

4.1 Hierarchical Modeling Using Sub-model

In using hierarchical modeling it is necessary to build appropriate *sub-models* that can accurately represent the thermal behavior of the original complex *component-model*. To create a sub-model the original *detailed* model of the component is used [5]. This model would accurately represent or reconstruct the physical geometry of the component very closely. A detailed model which physically models the actual device geometry can be created by using a numerical simulator, such as, *Atar*. This model would be a discretized version of the physical model and can be mathematically described by a large set of coupled non-linear equations. A detailed model can predict the temperatures of the

various elements within the package (including junction, case, and leads) accurately regardless of the thermal environment in which it is placed, i.e., this model is, by definition, boundary condition independent (BCI). We wish to create or define a *sub-model* from this detailed model.

A sub-model replaces the complex detailed component-model with a simple mathematical relationship between port temperatures and port heat-flows. To create a sub-model it is needed to extract this relationship from the detailed model. It is worthwhile to mention that the sub-models should also be able to produce all the temperatures of interest in the detailed model, such as, junction temperatures. To create a complete simulation a sub-model is linked to a detailed numerical model called *base-model* as shown in Figure 4.1. This figure shows a base-model consisting of substrate and metallization, and two components. One component is a fully detailed component-model and the other is represented as a sub-model. This is an example of an *Atar mixed-model*.

Figure 4.1: *Atar* Mixed-model Showing a Base-model, a Detailed Component-model and a Sub-model

The interface or contact surfaces between the sub-model and the base-model are designated as thermal ports where the thermal ports allow the linking between the models. As a result, the sub-model can exchange heat with the base-model.

The definition of the sub-model requires the geometric specification of the ports on the detailed component-model and of the temperatures of interest. Inputs for the sub-model are therefore port temperatures (T_p 's), input power (P) and applied boundary conditions (BC 's). Outputs are port heat-flows (I_p 's) and temperatures of interest (T_j 's). In general these relationships are non-linear and we have:

$$\vec{I}_p = f(\vec{T}_p, \vec{P}, \vec{BC}) \quad (4.1)$$

$$\vec{T}_j = g(\vec{T}_p, \vec{P}, \vec{BC}) \quad (4.2)$$

These relationships [4] can be mathematically extracted efficiently for linear models leading to

$$\vec{I}_p = G_p \vec{T}_p + \vec{F}_p \quad (4.3)$$

$$\vec{T}_j = A_{jp} \vec{T}_p + \vec{T}_{jp} \quad (4.4)$$

where, $G_p \in \mathbb{R}^{n_p \times n_p}$ is the discretized thermal conductance matrix, $\vec{F}_p \in \mathbb{R}^{n_p \times 1}$ is the source vector representing internal power generation and applied boundary conditions,

$A_{pp} \in \mathfrak{R}^{n_p \times n_p}$ is the transformation matrix and $\vec{T}_{pp} \in \mathfrak{R}^{n_p \times 1}$ is the source temperature. For non-linear models, the relationships can be extracted from the detailed model using neural network training.

A primary concern in the definition of the sub-model is its accuracy. The accuracy of a sub-model depends on the number of ports as well as the geometric port configuration. In general, increasing the number of ports will increase the accuracy. However, as the prime consequence of the port is the imposition of constant temperature region over the port, the choice of port geometry is very important. To determine the accuracy of a given sub-model port configuration, two *Atar* models are built: (1) A fully detailed model of the component and base-model. (2) A mixed-model using a detailed base-model and a sub-model for the component. These two models can then be compared with respect to the temperature distribution in the base and the temperatures of interest in the component.

In order to evaluate the consequences of using ports, the error is calculated for various points of interest for many port configurations of the sub-model using Equation (4.5).

$$Error = \frac{|T_{det} - T_{sub}|}{T_{det} - 300} \quad (4.5)$$

where, T_{det} is the temperature at a point of interest in the fully detailed model and T_{sub} is the corresponding temperature of the mixed-model or sub-model. Previous work [34] in this area confirms that the accuracy of a sub-model increases with the increase in the

number of ports. This is due to the fact that more information in the original model is captured as a greater number of ports are employed.

4.2 Sub-model Definition Using *Atar*

The first task in the creation of a non-linear sub-model from a component-model is an evaluation of the error inherent in various port configurations and the appropriate selection of a particular port configuration. In order to select an appropriate sub-model for neural network modeling linear simulations $\left(\text{with } K = K_{300} \right)$ have been performed on both a detailed model and a mixed-model using a variety of linear sub-models built using *Atar*. The main purposes of performing these simulations discussed are:

- To evaluate the use of each sub-model for a variety of boundary conditions applied to the base-model.
- To determine the importance of the presence of ports in effecting the temperatures in the base-model and the component-model.
- To determine the minimum number of inputs (ports) that can produce an accurate sub-model with which to build a non-linear neural network model that can represent the accurate thermal behavior of the original model.

It is assumed here that for the evaluation of the port configurations using linear sub-models will provide a sufficiently accurate response for determining the number of inputs

for non-linear modeling. Linear sub-models can be generated very quickly using *Atar* and generate temperatures at different points of interest for a variety of BCs. In order to determine the minimum numbers of inputs required for neural network modeling, errors at different temperature points are calculated using Equation (4.5) for different port configurations of linear sub-models with respect to that of the detailed model.

It should be noted here that it is not desired to have a large number of inputs for neural network modeling because a large number of inputs would lead to a network with large input dimensions and a prohibitive amount of training. On the other hand, if the number of inputs is too few, the sub-model may not be able represent the original model accurately. Therefore, the number of inputs (and configuration of the port geometry) has to be selected accordingly. After selecting the number of inputs for neural network modeling from the linear simulations, a large number of data is generated for a variety of applied port temperatures and input power by performing non-linear simulation of the *Atar* component-model.

The outputs generated from *Atar* simulation for neural network modeling include the maximum temperature of a simple linear solution of the model, maximum temperature of a non-linear solution, port heat-flows and temperatures at different points that might be of interest. It is worthwhile to mention that increasing the number of outputs for neural network model does not lead to a more complicated model analysis. Therefore, the number of outputs might be increased when an in depth study on the model is necessary.

4.3 Linear Simulation Results for Package Models

This section presents the simulation results for different IC components and packages, chosen from different technologies, as follows: (a) A Gallium Nitride (GaN) on SiC power package amplifier, (b) A Gallium Arsenide (GaAs) based power amplifier and (c) Ceramic-Ball-Grid-Array (CBGA) single-chip package. These models have been chosen to provide a broad range of geometries and applications to enable an evaluation of the neural network sub-modeling technique over a range of situations.

4.3.1 GaN Based Power Package Amplifier

It has been chosen to model non-linear GaN power cells consisting of GaN mesa structures as sub-models. These sub-models are then attached to a base-model of a Si substrate. Figure 4.2 shows a single cell of a GaN based power cell amplifier with six fingers on a single metal substrate. Figure 4.3 (a) shows a detailed GaN component-model attached to the base-model used to evaluate the sub-model and Figure 4.3 (b) shows the same model but with a sub-model attached to the base-model.

To evaluate the sub-model performance for a wide variety of heat-flow conditions both a detailed model and a sub-model of the GaN power amplifier have been simulated using *Atar* for six different simulation scenarios as shown in Table 4.1. For these simulations the boundary conditions on the sides of the base-model have been varied to produce different thermal conditions for the sub-model.

Figure 4.2: GaN Based Power Amplifier Mesa Structure

(a)

(b)

Figure 4.3: (a) GaN Component-model Attached to a Base-model (b) GaN Sub-model Attached to a Base-model

Table 4.1: Different Scenarios for Linear Simulation of GaN Model

Case-1	P=0.002W	T = 300K for <i>back, left, right, up</i> and <i>down</i> -sides
Case-2		T = 300K for <i>back</i> -side; no heat-flow for <i>other sides</i>
Case-3		T = 300K for <i>left</i> -side; no heat-flow for <i>other sides</i>
Case-4		T = 300K for <i>right</i> -side; no heat-flow for <i>other sides</i>
Case-5		T = 300K for <i>up</i> -side; no heat-flow for <i>other sides</i>
Case-6		T = 300K for <i>down</i> -side; no heat-flow for <i>other sides</i>

Basic ports of the model include the following regions: (a) The three metal connections (b) Four regions for the bottom of the GaN model as shown in Figure 4.4 (a) and Figure 4.4 (b). To determine the effect of port configuration on the performance of the sub-model six different port configurations of the sub-model have been tested as follows:

- Nine Ports – Four ports on the bottom, two ports for each of the two metal contacts at the back, i.e., a total of four ports and one port for the metal contact on the side forms nine different ports.
- Seven Ports – Four ports on the bottom and three metal ports form seven different ports.
- Five Ports – Four points in the bottom form four ports while all the metal points together form another single port.
- Four Ports – Three metal points form three different ports while the bottom of the sub-model forms another single port.
- Two Ports – All the metal points together form one port and the bottom of the sub-model forms another port.
- One Port – All the points together (three points in the metal and the rest six points) form a single port.

Figure 4.4: GaN Mixed-model Showing (a) Metal Ports (b) Metal Ports and Ports at the Bottom (c) Different Temperature Points (I1_1 – I3_6) of Interest

The outputs of the linear simulation obtained from *Atar* for both detailed and sub-model include the temperatures at the different points that might be of interest. These points (shown in Figure 4.4) are as follows: three points in each of the six fingers, i.e., a total of eighteen points; three metal points; and four points in the bottom. The simulation results for this model for case – 2 in Table 4.1 are shown in Table 4.2 and Table 4.3.

Table 4.2: The Output Temperatures (for Case – 2 in Table 4.1) of GaN Model

Points	T_detail (K)	T_9port (K)	T_7port (K)	T_5port (K)	T_4port (K)	T_2port (K)	T_1port (K)
<i>I1_1</i>	314.54	314.90	314.86	314.76	314.85	314.77	314.77
<i>I1_2</i>	315.56	315.82	315.82	315.74	315.80	315.73	315.74
<i>I1_3</i>	314.74	315.05	315.02	314.97	314.98	314.94	314.94
<i>I1_4</i>	315.08	315.36	315.27	315.17	315.27	315.18	315.18
<i>I1_5</i>	316.33	316.49	316.46	316.38	316.44	316.37	316.37
<i>I1_6</i>	315.31	315.52	315.44	315.40	315.41	315.37	315.37
<i>I2_1</i>	315.52	315.52	315.39	315.28	315.39	315.29	315.29
<i>I2_2</i>	316.83	316.70	316.64	316.56	316.63	316.56	316.56
<i>I2_3</i>	315.74	315.68	315.54	315.50	315.52	315.48	315.48
<i>I2_4</i>	315.72	315.64	315.50	315.39	315.52	315.41	315.40
<i>I2_5</i>	316.65	316.49	316.42	316.35	316.42	316.35	316.35
<i>I2_6</i>	315.75	315.66	315.53	315.50	315.52	315.49	315.48
<i>I3_1</i>	315.24	315.49	315.37	315.27	315.40	315.30	315.29
<i>I3_2</i>	316.44	316.56	316.48	316.42	316.50	316.43	316.43
<i>I3_3</i>	315.43	315.63	315.53	315.52	315.52	315.50	315.50
<i>I3_4</i>	315.00	315.23	315.13	315.05	315.17	315.08	315.07
<i>I3_5</i>	315.71	315.84	315.77	315.71	315.79	315.72	315.72
<i>I3_6</i>	314.97	315.18	315.10	315.11	315.10	315.09	315.09
<i>PM1</i>	311.75	311.91	311.32	310.94	311.34	310.95	310.85
<i>PM2</i>	311.80	311.71	311.04	310.77	311.00	310.76	310.64
<i>PM3</i>	308.02	307.92	307.90	310.50	307.90	310.49	310.33
<i>PB1</i>	310.54	311.01	311.07	310.98	311.07	311.00	311.01
<i>PB2</i>	310.62	310.97	311.02	310.96	310.97	310.91	310.91
<i>PB3</i>	310.64	311.04	311.00	310.93	311.05	310.98	310.99
<i>PB4</i>	310.74	311.03	310.98	310.94	310.98	310.92	310.92

Table 4.3: Calculated Errors for Output Temperatures (for Case – 2 in Table 4.1) of GaN Model

Points	E_9ports	E_7ports	E_5ports	E_4ports	E_2ports	E_1port
<i>I1_1</i>	0.024759	0.022008	0.015131	0.021320	0.015818	0.015818
<i>I1_2</i>	0.016710	0.016710	0.011568	0.015424	0.010925	0.011568
<i>I1_3</i>	0.021031	0.018996	0.015604	0.016282	0.013569	0.013569
<i>I1_4</i>	0.018568	0.012599	0.005968	0.012599	0.006631	0.006631
<i>I1_5</i>	0.009798	0.007961	0.003062	0.006736	0.002449	0.002449
<i>I1_6</i>	0.013717	0.008491	0.005879	0.006532	0.003919	0.003919
<i>I2_1</i>	0.000000	0.008376	0.015464	0.008376	0.014820	0.014820
<i>I2_2</i>	0.007724	0.011289	0.016043	0.011884	0.016043	0.016043
<i>I2_3</i>	0.003812	0.012706	0.015248	0.013977	0.016518	0.016518
<i>I2_4</i>	0.005089	0.013995	0.020992	0.012723	0.019720	0.020356
<i>I2_5</i>	0.009610	0.013814	0.018018	0.013814	0.018018	0.018018
<i>I2_6</i>	0.005714	0.013968	0.015873	0.014603	0.016508	0.017143
<i>I3_1</i>	0.016404	0.008530	0.001969	0.010499	0.003937	0.003281
<i>I3_2</i>	0.007299	0.002433	0.001217	0.003650	0.000608	0.000608
<i>I3_3</i>	0.012962	0.006481	0.005833	0.005833	0.004537	0.004537
<i>I3_4</i>	0.015333	0.008667	0.003333	0.011333	0.005333	0.004667
<i>I3_5</i>	0.008275	0.003819	0.000000	0.005092	0.000637	0.000637
<i>I3_6</i>	0.014028	0.008684	0.009352	0.008684	0.008016	0.008016
<i>PM1</i>	0.013617	0.036596	0.068936	0.034894	0.068085	0.076596
<i>PM2</i>	0.007627	0.064407	0.087288	0.067797	0.088136	0.098305
<i>PM3</i>	0.012469	0.014963	0.309227	0.014963	0.307980	0.288030
<i>PB1</i>	0.044592	0.050285	0.041746	0.050285	0.043643	0.044592
<i>PB2</i>	0.032957	0.037665	0.032015	0.032957	0.027307	0.027307
<i>PB3</i>	0.037594	0.033835	0.027256	0.038534	0.031955	0.032895
<i>PB4</i>	0.027002	0.022346	0.018622	0.022346	0.016760	0.016760

The results for other cases mentioned in Table 4.1 are shown Tables A.1.1 to A.1.10 in Appendix A. Table 4.4 shows the average error for all the temperatures of interest for the different cases mentioned in Table 4.1.

Table 4.4: Average Errors for Output Temperatures of GaN Model

Ports Cases	E_9 Ports	E_7 Ports	E_5 Ports	E_4 Ports	E_2 Ports	E_1 Port
<i>1</i>	0.026955	0.032180	0.066311	0.032294	0.066244	0.065490
<i>2</i>	0.015468	0.018385	0.030626	0.018445	0.030475	0.030523
<i>3</i>	0.023606	0.028320	0.050497	0.028432	0.050477	0.050087
<i>4</i>	0.022987	0.027563	0.058763	0.027710	0.058538	0.058086
<i>5</i>	0.022775	0.027646	0.053027	0.027747	0.053106	0.052871
<i>6</i>	0.024264	0.028299	0.052756	0.028191	0.052340	0.051994
<i>Average</i>	0.022676	0.027066	0.051997	0.027137	0.051863	0.051509

It has been observed that the nine-port configuration gives the best result, i.e., less error for all the cases. For five-port, two-port and one-port configurations, the errors are higher than that of the seven-port and four-port configurations. It can be concluded that the nine-port, seven-port and four-port configurations give less error, but the number of ports for the nine-port and seven-port configurations are too high for neural network modeling. Considering all the port configurations, the four-port configuration has been primarily selected for neural network modeling. However, in addition, the five-port configuration has also been investigated.

4.3.2 GaAs Based Power Amplifier

The second example is for a GaAs power cell. For this case a piece of substrate is defined as a sub-model. The component-model is shown in Figure 4.5 (a) and is composed of a $32 \times 32 \times 32 \mu\text{m}$ piece of substrate and a four finger FET (shown in Figure 4.5 (a)). Figure 4.5 (b) shows a simple power cell of GaAs based power amplifier having metal connections placed in a simple substrate. To evaluate the sub-model performance for a wide variety of heat-flow conditions both a detailed model and a sub-model of the GaAs power amplifier have been simulated using *Atar* for six different simulation scenarios as shown in Table 4.5. For these simulations the boundary conditions on the sides of the base-model have been varied to produce different thermal conditions for the sub-model.

Table 4.5: Different Scenarios for Linear Simulation of GaAs Model

Case-1	P=0.075W	T = 300K for <i>back, left, right, up</i> and <i>down</i> -side
Case-2		T = 300K for <i>back</i> -side; <i>Other sides free</i>
Case-3		T = 300K for <i>left</i> -side; <i>Other sides free</i>
Case-4		T = 300K for <i>right</i> -side; <i>Other sides free</i>
Case-5		T = 300K for <i>up</i> -side; <i>Other sides free</i>
Case-6		T = 300K for <i>down</i> -side; <i>Other sides free</i>

Figure 4.6 shows the GaAs sub-model with boundary condition where the dark green in the middle represents links to the ports, red color regions represents no heat-flow and light green towards the right-side of the figure represents fixed BC.

(a)

(b)

Figure 4.5: GaAs Power Amplifier (a) Component-model Showing Metal Ports and Ports at the Sides (b) Sub-model Attached to a Base-model

Figure 4.6: GaAs Sub-model Showing the Boundary Condition

Basic ports of this model include the following regions: (a) Four metal regions (b) Five regions for the five sides of the substrate as shown in Figure 4.5 (a). Different port configurations applied to sub-model are:

- Nine ports – Five points (PB1 – PB5) in the five different sides of the sub-model and the four metal points (PM1 – PM4) form nine different ports.
- Five ports – Four metal points form four different ports while the substrate of the sub-model forms another single port.
- Two ports – All the metal points together form one port and the substrate of the sub-model forms another single port.
- One port – All the points together (four points in the metal and the rest five points) form a single port.

Temperatures obtained at different points of the detailed and sub-model are: three points in each of the four fingers, i.e., a total of twelve points; four metal points; and five other points in five sides involved in the port configuration of the sub-model. The simulation results for this model for case – 3 in Table 4.5 are shown in Table 4.6 and Table 4.7.

Table 4.6: The Output Temperatures (for Case – 3 in Table 4.5) of GaAs Model

Points	T_detailed (K)	T_9ports (K)	T_5ports (K)	T_2ports (K)	T_1port (K)
<i>I1_1</i>	669.76	666.10	665.99	666.18	665.19
<i>I1_2</i>	1009.55	1005.70	1005.60	1005.80	1004.70
<i>I1_3</i>	948.53	944.73	944.56	944.59	943.79
<i>I2_1</i>	683.48	679.06	678.37	678.19	677.46
<i>I2_2</i>	1024.62	1020.10	1019.40	1019.10	1018.40
<i>I2_3</i>	963.21	958.63	957.87	957.54	957.02
<i>I3_1</i>	688.85	683.54	682.33	681.86	681.10
<i>I3_2</i>	1031.11	1025.70	1024.40	1023.80	1023.00
<i>I3_3</i>	968.06	962.53	961.26	960.64	960.06
<i>I4_1</i>	670.41	664.15	662.39	661.20	660.03
<i>I4_2</i>	1008.85	1002.40	1000.60	999.20	997.90
<i>I4_3</i>	950.16	943.71	941.89	940.69	939.74
<i>PM1</i>	364.48	359.00	359.26	368.62	355.35
<i>PM2</i>	392.75	384.63	382.58	369.23	355.99
<i>PM3</i>	389.28	380.31	379.35	369.90	356.50
<i>PM4</i>	363.89	359.06	358.34	367.27	354.36
<i>PB1</i>	353.72	354.72	355.34	355.17	355.73
<i>PB2</i>	364.14	358.18	355.59	355.38	355.94
<i>PB3</i>	357.57	356.29	355.31	355.13	355.70
<i>PB4</i>	356.03	355.58	354.94	354.79	355.33
<i>PB5</i>	364.62	361.15	360.36	360.19	360.65

Table 4.7: Calculated Errors for Output Temperatures (for Case – 3 in Table 4.5) of GaAs Model

Points	E_9ports	E_5ports	E_2ports	E_1port
<i>I1_1</i>	0.009898	0.010196	0.009682	0.012359
<i>I1_2</i>	0.005370	0.005553	0.005356	0.006892
<i>I1_3</i>	0.005859	0.006122	0.006075	0.007309
<i>I2_1</i>	0.011526	0.013325	0.013795	0.015698
<i>I2_2</i>	0.006252	0.007245	0.007673	0.008653
<i>I2_3</i>	0.006906	0.008052	0.008549	0.009333
<i>I3_1</i>	0.013656	0.016767	0.017976	0.019931
<i>I3_2</i>	0.007441	0.009137	0.010012	0.011065
<i>I3_3</i>	0.008278	0.010179	0.011107	0.011975
<i>I4_1</i>	0.016900	0.021652	0.024864	0.028023
<i>I4_2</i>	0.009043	0.011596	0.013614	0.015448
<i>I4_3</i>	0.009921	0.012720	0.014566	0.016027
<i>PM1</i>	0.084988	0.080955	0.064206	0.141594
<i>PM2</i>	0.087547	0.109650	0.253585	0.396334
<i>PM3</i>	0.100470	0.111223	0.217070	0.367159
<i>PM4</i>	0.075599	0.086868	0.052903	0.149163
<i>PB1</i>	0.018615	0.030156	0.026992	0.037416
<i>PB2</i>	0.092922	0.133302	0.136576	0.127845
<i>PB3</i>	0.022234	0.039257	0.042383	0.032482
<i>PB4</i>	0.008031	0.019454	0.022131	0.012493
<i>PB5</i>	0.053699	0.065924	0.068555	0.061436

The results for other cases mentioned in Table 4.5 are shown in Tables A.2.1 to A.2.10 in Appendix A. Table 4.8 shows the average error for all the temperatures of interest for the different cases mentioned in Table 4.5.

Table 4.8: Average Errors for Output Temperatures of GaAs Model

Ports Cases	E_9 Ports	E_5 Ports	E_2 Ports	E_1 Port
<i>1</i>	0.040888	0.041829	0.067634	0.122851
<i>2</i>	0.038349	0.039401	0.063944	0.117558
<i>3</i>	0.031198	0.038540	0.048937	0.070887
<i>4</i>	0.035363	0.042642	0.048987	0.076093
<i>5</i>	0.038159	0.046619	0.073872	0.083669
<i>6</i>	0.030938	0.037814	0.037099	0.069895
<i>Average</i>	0.035816	0.041141	0.056745	0.090159

Figure 4.7: Temperature Contour for the Sub-model of GaAs Model (Fixed BC in the Front-side of the Figure)

Figure 4.7 shows the temperature contour for the mixed-model. It has been observed from Table 4.8 that the error becomes higher with the decrease in number of ports. It has also been observed that the nine-port configuration always gives better result, i.e., less error for all temperatures and with different boundary conditions. For one-port and two-port configurations, the errors are higher as compared to that of five-port configuration. It can be concluded that the nine-port configuration gives less error but the number of ports for the nine-port configuration are too high for neural network modeling. Considering all the port configurations, the five-port configuration has been selected as the appropriate choice for neural network modeling.

4.3.3 Package Model

The final example is a BGA package for the component model mounted on a PCB substrate. An additional input to the component-model is the heat-flow off the top characterized by α . Figure 4.8 shows a single package with a simple substrate. The package model has 64 lead bumps which are located at the back-side of the model. Six different conditions for which simulations have been performed on sub-model as well as detailed model of package model are shown in Table 4.9.

Table 4.9: Different Scenarios for Linear Simulation of Package Model

Case-1	P=0.5W	$\alpha_{\text{top}} = 0$ W/ $\mu\text{m}^2\text{K}$	T = 300K for <i>right</i> -side; no heat-flow for <i>back</i> -side
Case-2			T = 300K for <i>back</i> -side; no heat-flow for <i>right</i> -side
Case-3		$\alpha_{\text{top}} = 10^{-3}$ W/ $\mu\text{m}^2\text{K}$	T = 300K for <i>right</i> -side; no heat-flow for <i>back</i> -side;
Case-4			T = 300K for <i>back</i> -side; no heat-flow for <i>right</i> -side;
Case-5		$\alpha_{\text{top}} = 10^{-5}$ W/ $\mu\text{m}^2\text{K}$	T = 300K for <i>right</i> -side; no heat-flow for <i>back</i> -side;
Case-6			T = 300K for <i>back</i> -side; no heat-flow for <i>right</i> -side;

Basic port configurations of the package model include three regions having three rings:

(a) Outer ring (b) Middle ring (c) Inner ring. The Different port configurations used for the sub-model are as follows:

- Three Ports – Three rings; where the single point in the centre of the inner ring of the sub-model forms one port, the eight points of the middle ring form the second port and the sixteen points of the outer ring of the sub-model form the third port.

Figure 4.9 (a) shows the top view of the package model with three ports.

- Two Ports – Two rings; where the single point in the centre of the inner ring form one port and the rest twenty four points (eight points of the middle ring and sixteen points of the outer ring) form another port.
- One Port – All the twenty five points together form a single port.

(a)

(b)

Figure 4.8: $\frac{1}{2}$ View of Package Model (a) Sub-model Attached to Base-model (b) Component-model Attached to Base-model

(a)

(b)

Figure 4.9: Top View of Package Model Showing (a) Three Ports (b) Different Points (P1 – P16) of Interest

The outputs generated for this model are the temperatures in the twenty five points involved in the port configurations and the temperatures at sixteen other points (shown in Figure 4.9 (b)) of interest of the model. Errors have been calculated for all the above mentioned temperatures of the sub-model for different port configurations with respect to the corresponding temperatures of the detailed model. The simulation results for this model for case – 5 in Table 4.9 are shown in Table 4.10.

Table 4.10: Output Temperatures and Corresponding Errors (for Case – 5 in Table 4.9) of Package Model

Point	T_detail (K)	T_3ports (K)	E_3ports	T_2ports (K)	E_2ports	T_1port (K)	E_1port
<i>S1</i>	301.82	301.86	0.021978	301.98	0.087912	302.04	0.120879
<i>S2</i>	302.02	301.95	0.034653	302.02	0.000000	302.07	0.024752
<i>S3</i>	302.11	301.98	0.061611	302.03	0.037915	302.08	0.014218
<i>S4</i>	301.99	301.94	0.025126	302.02	0.015075	302.07	0.040201
<i>S5</i>	301.80	301.85	0.027778	301.97	0.094444	302.02	0.122222
<i>S6</i>	301.95	301.91	0.020513	301.99	0.020513	302.04	0.046154
<i>S7</i>	302.32	302.26	0.025862	302.06	0.112069	302.09	0.099138
<i>S8</i>	302.54	302.35	0.074803	302.12	0.165354	302.09	0.177165
<i>S9</i>	302.26	302.23	0.013274	302.05	0.092920	302.08	0.079646
<i>S10</i>	301.91	301.88	0.015707	301.98	0.036649	302.03	0.062827
<i>S11</i>	301.96	301.90	0.030612	301.97	0.005102	302.02	0.030612
<i>S12</i>	302.45	302.30	0.061224	302.08	0.151020	302.07	0.155102
<i>S13</i>	302.78	302.63	0.053957	302.44	0.122302	302.08	0.251799
<i>S14</i>	302.37	302.27	0.042194	302.06	0.130802	302.06	0.130802
<i>S15</i>	301.91	301.87	0.020942	301.95	0.020942	302.00	0.047120
<i>S16</i>	301.77	301.82	0.028249	301.91	0.079096	301.96	0.107345
<i>S17</i>	302.09	302.15	0.028708	301.98	0.052632	302.02	0.033493
<i>S18</i>	302.27	302.22	0.022026	302.02	0.110132	302.03	0.105727
<i>S19</i>	302.04	302.13	0.044118	301.98	0.029412	302.01	0.014706
<i>S20</i>	301.73	301.80	0.040462	301.89	0.092486	301.94	0.121387
<i>S21</i>	301.49	301.66	0.114094	301.77	0.187919	301.82	0.221477
<i>S22</i>	301.66	301.74	0.048193	301.83	0.102410	301.88	0.132530
<i>S23</i>	301.73	301.76	0.017341	301.84	0.063584	301.89	0.092486
<i>S24</i>	301.64	301.73	0.054878	301.83	0.115854	301.87	0.140244
<i>S25</i>	301.46	301.64	0.123288	301.75	0.198630	301.80	0.232877
<i>P1</i>	301.24	301.22	0.016129	301.19	0.040323	301.19	0.040323
<i>P2</i>	302.36	302.34	0.008475	302.30	0.025424	302.29	0.029661
<i>P3</i>	302.36	302.34	0.008475	302.30	0.025424	302.29	0.029661
<i>P4</i>	301.24	301.22	0.016129	301.19	0.040323	301.19	0.040323

<i>P5</i>	302.36	302.34	0.008475	302.30	0.025424	302.29	0.029661
<i>P6</i>	306.11	306.08	0.004910	306.05	0.009820	306.02	0.014730
<i>P7</i>	306.11	306.08	0.004910	306.05	0.009820	306.02	0.014730
<i>P8</i>	302.36	302.34	0.008475	302.30	0.025424	302.29	0.029661
<i>P9</i>	302.36	302.34	0.008475	302.30	0.025424	302.29	0.029661
<i>P10</i>	306.11	306.08	0.004910	306.05	0.009820	306.02	0.014730
<i>P11</i>	306.11	306.08	0.004910	306.05	0.009820	306.02	0.014730
<i>P12</i>	302.36	302.34	0.008475	302.30	0.025424	302.29	0.029661
<i>P13</i>	301.23	301.22	0.008130	301.19	0.032520	301.19	0.032520
<i>P14</i>	302.35	302.34	0.004255	302.30	0.021277	302.29	0.025532
<i>P15</i>	302.35	302.34	0.004255	302.30	0.021277	302.29	0.025532
<i>P16</i>	301.23	301.22	0.008130	301.19	0.032520	301.19	0.032520

The results for other cases mentioned in Table 4.9 are shown in Table A.3.1 to Table A.3.5 in Appendix A. It can be observed from Table 4.10 and also from Table A.3.1 to Table A.3.5 that the errors become higher with the decrease in number of ports. Table 4.11 shows the average error for all the temperatures of interest for the different cases mentioned in Table 4.9.

Table 4.11: Average Errors for Output Temperatures of Package Model

Ports Cases	E_3 Ports	E_2 Ports	E_1 Port
<i>1</i>	0.023581	0.031520	0.034833
<i>2</i>	0.021768	0.051963	0.063044
<i>3</i>	0.029430	0.061528	0.075435
<i>4</i>	0.054150	0.137610	0.165352
<i>5</i>	0.028759	0.061103	0.074111
<i>6</i>	0.053851	0.135705	0.163926
<i>Average</i>	0.035257	0.079905	0.096117

It has been observed from Table 4.11 that the three-port configuration always provides better results for all temperatures and with different boundary conditions as compared to that of one-port and two-port configurations. Consequently, the three-port configuration has been selected as the appropriate choice for neural network modeling.

4.4 Summary

It has been observed that the average errors of temperatures for different port configurations for all the three models are within satisfactory limit (For GaN, GaAs and Package model the average errors are 2% – 5%, 4% – 9% and 3% – 10% respectively). Accordingly, the best port configuration of sub-model selected for neural network modeling for GaN, GaAs and Package model have been four-port, five-port and three-port configuration respectively. After deciding the best port configuration for each model, i.e., the inputs for neural network modeling, non-linear simulation have been performed on these three models and subsequently, a large number of data have been generated. These data have been used to train the neural model. The next chapter presents the results obtained from neural network modeling.

Chapter 5

Creation and Training of Neural Network Modeling

In this chapter, neural network models with three-layer and four-layer perceptrons are developed with both back propagation and conjugate gradient training method using the tool called *Neuromodeler* for each of the three models mentioned in Chapter 4. Afterwards, the qualities of these models are evaluated by testing them with a set of testing data.

5.1 Neural Network Modeling

The primary steps to develop a neural network model are to identify the inputs and outputs of the problem to be modeled and to generate data for training and testing the model. In this thesis, the inputs for the neural network model have been decided from *Atar* simulations described in Section 4.2 and Section 4.3. The inputs of the neural model have been chosen as the port temperatures and power while the outputs have been chosen as the maximum temperature of a simple linear solution of the model, maximum temperature of a non-linear solution, port heat-flows for each of the input ports and

temperatures at different points that might be of interest as shown in Figure 5.1. As indicated in Chapter 2, the modeling tool, *Neuromodeler* has been used to build the model. The main steps of the neural network modeling have been:

- To generate a large set of training data in order to build the neural network model for each of the three models so that the neural model could represent the original problem behavior accurately.
- To train three-layer perceptrons as well as four-layer perceptrons networks with both back propagation and conjugate gradient training methods.
- To evaluate the quality of the trained model by testing it with a different set of data for each model.
- To evaluate the performance of the two training algorithms on each model by comparing the training and testing error.

Figure 5.1: Inputs and Outputs of the Developed Neural Network Model

The training and testing results for neural network-based modeling for all the three models mentioned earlier is presented in the subsequent sections.

5.2 GaN Based Power Package Amplifier

It was decided from *Atar* simulation mentioned in Chapter 4 that the four-port configuration would be the best choice for neural network modeling for GaN based power package amplifier model. In addition, the five-port configuration is to be investigated. Consequently, the inputs of this model for neural network modeling have been selected as the different port temperatures (*Bot*, *M1*, *M2* and *M3*, i.e., one port at the bottom and three metal ports for four-port configuration and *Port1-Port5*, i.e., four ports at the bottom and one metal port for five-port configuration) and the power. The port temperatures have been varied from 300 – 340K (with an increase of 10K) while the power has been varied from 0.02 – 0W (with a decrease of 0.005W). The outputs of this model include the maximum temperature (*T-linear*) of a simple linear solution of the model, maximum temperature (*T-nonlinear*) of a non-linear solution, port heat-flows (*T-bot* and *TM1-TM3* for four-port configuration and *TP1-TP5* for five-port configuration) for each of the input ports and temperatures at 37 different points that might be of interest. A total of 3125 and 15625 training data (where each data represents a set of all the inputs and outputs) have been generated for four-port and five-port configuration respectively by performing a non-linear simulation using *Atar*. Afterwards, a separate set of randomly generated data (approximately 1500) has been used to evaluate the performance of the trained model.

5.2.1 Training of GaN Model with Four-Port Configuration

The GaN model with four-port configuration has been trained in four ways as follows,

- 1) Three-layer perceptrons network with back propagation training method.
- 2) Three-layer perceptrons network with conjugate gradient training method.
- 3) Four-layer perceptrons network with back propagation training method.
- 4) Four-layer perceptrons network with conjugate gradient training method.

1) Three-layer with Back Propagation: The number of hidden neurons in the hidden layer of the three-layer perceptrons network has been chosen (automatically chosen by *Neuromodeler*) as 20. The initial conditions (automatically chosen by *Neuromodeler*) of the training method have been: maximum number of epochs: 100, learning rate: 0.001 and momentum factor: 0. With these initial conditions, the final training error obtained has been 0.006987657 at 100 epochs (the first training has been performed for 100 epochs where the number of epochs was automatically set by *Neuromodeler*). It has been observed that as the network was trained further, the final training error decreased with the increase in epochs. At the end of 1000 epochs (after training the network for 10 times, the number of epochs reached 1000) the final training error has been obtained as 0.005296763. Figure 5.2 shows the training error against the first 500 epochs. As mentioned in Chapter 3, the training error is defined as,

$$E_{T_r}(\vec{w}) = \left[\frac{1}{\text{size}(T_r) \cdot m} \sum_{k \in T_r} \sum_{j=1}^m \left| \frac{y_j(x_k, \vec{w}) - d_{jk}}{d_{\max,j} - d_{\min,j}} \right|^p \right]^{1/p} \quad (5.1)$$

where $y_j(x_k, \vec{w})$ is the j^{th} output of the neural network for input sample x_k , d_k is the measured/simulated output for $\vec{y}$ for the input x_k , T_r is the index set of training data, $k \in T_r$, m is the dimension of the output $\vec{y}$, d_{jk} is the j^{th} element of d_k , p represents least p^{th} optimization, $d_{\max,j}$ and $d_{\min,j}$ are the maximum and minimum values of the j^{th} element of all vectors of d_k .

2) Three-layer with Conjugate Gradient: The number of hidden neurons in the hidden layer of the three-layer perceptrons network has been chosen (automatically chosen by *Neuromodeler*) as 20. The initial conditions (automatically chosen by *Neuromodeler*) of the training method have been: maximum number of epochs: 200, function error tolerance: $1e^{-4}$ and model parameter tolerance: $1e^{-4}$. With these initial conditions, the final training error obtained has been 0.00457244 at 200 epochs (the first training has been performed for 200 epochs where the number of epochs was automatically set by *Neuromodeler*). It has been observed that as the network was trained further, the final training error decreased with the increase in epochs. At the end of 412 epochs (after training the network for 10 times, the number of epochs reached 412) the final training error has been obtained as 0.003389. Figure 5.2 shows the training error against the first 412 epochs.

3) Four-layer with Back Propagation: The number of hidden neurons in the 1st and 2nd hidden layer of the four-layer perceptrons network have been chosen (automatically chosen by *Neuromodeler*) as 5 and 3 respectively. The initial conditions (automatically chosen by *Neuromodeler*) of the training method have been: maximum number of epochs: 200, learning rate: 0.001 and momentum factor: 0. With these initial conditions, the final training error obtained has been 0.0270021 at 200 epochs (the first training has been performed for 200 epochs where the number of epochs was automatically set by *Neuromodeler*). It has been observed that as the network was trained further, the final training error decreased with the increase in epochs. At the end of 1200 epochs (after training the network for 10 times, the number of epochs reached 1200) the final training error has been obtained as 0.0264888. Figure 5.2 shows the training error against the first 500 epochs.

4) Four-layer with Conjugate Gradient: The number of hidden neurons in the 1st and 2nd hidden layer of the four-layer perceptrons network have been chosen (automatically chosen by *Neuromodeler*) as 5 and 3 respectively. The initial conditions (automatically chosen by *Neuromodeler*) of the training method have been: maximum number of epochs: 200, function error tolerance: $1e^{-4}$ and model parameter tolerance: $1e^{-4}$. With these initial conditions, the final training errors obtained have been 0.0409873 and 0.0287286 at 110 (the first training has been performed for 110 epochs where the number of epochs was automatically set by *Neuromodeler*) and 240 epochs (after training the network for 10 times, the number of epochs reached 240) respectively. Figure 5.2 shows the training error against the 240 epochs.

The training errors obtained in the above mentioned ways are summarized in Table 5.1. As mentioned earlier, the number of hidden neurons and the initial conditions of the trainings have been automatically selected by the *Neuromodeler*.

Table 5.1: Training Errors of GaN Model with Four-Port Configuration

Layer/ Training	Hidden Neurons	Initial Condition	Initial Training Error (After 1 st Training)	Final Training Error (After 10 th Training)
3 layer BP	20	max. number of epochs: 100 learning rate: 0.001 momentum factor: 0	0.006987657 at 100 epochs	0.005296763 at 1000 epochs
3 layer CG	20	max. number of epochs: 200 function error tolerance: $1e^{-4}$ model parameter tolerance: $1e^{-4}$	0.004572440 at 200 epochs	0.003389000 at 412 epochs
4 layer BP	layer1: 5 layer2: 3	max. number of epochs: 200 learning rate: 0.001 momentum factor: 0	0.027002100 at 200 epochs	0.026488800 at 1200 epochs
4 layer CG	layer1: 5 layer2: 3	max. number of epochs: 200 function error tolerance: $1e^{-4}$ model parameter tolerance: $1e^{-4}$	0.040987300 at 110 epochs	0.028728600 at 240 epochs

Figure 5.2: Training Error of GaN Model with Four-Port Configuration for Different Training Methods and Structures

It has been observed from Figure 5.2 that after 200 epochs all the training curves become steady and the training errors stabilize. It has also been observed that at any epoch, the training error is less for three-layer perceptrons network than that of four-layer perceptrons network.

5.2.2 Testing of GaN Model with Four-Port Configuration

Once the neural network was built with the training data, the performance of the network has been tested with a separate set (unseen) of testing data. Table 5.2 shows the training and testing results for GaN model with four-port configuration.

Table 5.2: Training and Testing Results of GaN Model with Four-Port Configuration

Result Training	Epochs	Training Error	Average Testing Error	Maximum Testing Error	Correlation Coefficient
<i>3-layer BP</i>	1000	0.005296763	0.504973800	18.039429	0.99999640
<i>4-layer BP</i>	412	0.026488800	2.857109000	63.471737	0.99995610
<i>3-layer CG</i>	1200	0.003733890	0.376287160	14.991369	0.99999803
<i>4-layer CG</i>	240	0.028728600	3.035344100	66.668915	0.99995480

It can be observed from Table 5.2 that the average testing errors and maximum testing errors are also less for models with three-layer perceptrons network than that of four-layer perceptrons network. Also, as mentioned in Chapter 3, the correlation coefficient denotes the correlation between neural model and test data. Table 5.2 shows that the correlation coefficients are higher for models with three-layer perceptrons than that of four-layer perceptrons. Therefore, it can be concluded that the model is well trained with the conjugate gradient training as well as back propagation training method for three-

layer perceptrons network. Figure 5.3 represents the plots for average and maximum testing error vs. epoch for GaN model with three-layer perceptrons.

Figure 5.3 (a): Average Testing Error (%) vs. Epoch for GaN-4 Model with Three-Layer Perceptrons Using Back Propagation Training

Figure 5.3 (b): Maximum Testing Error (%) vs. Epoch for GaN-4 Model with Three-Layer Perceptrons Using Back Propagation Training

It has been observed from Figure 5.3 that the average and maximum testing errors decrease with the increase of number of training epochs. Therefore, it can be concluded that the network is not over trained. Table 5.3 shows the average and maximum testing errors for each of the outputs for GaN model with three-layer perceptrons.

Table 5.3: Testing Errors of GaN Model with Three-Layer Perceptrons and Four-Port Configuration

Output	Average Error (BP3)	Maximum Error (BP3)	Average Error (CG3)	Maximum Error (CG3)
<i>T-linear</i>	2.05835440	18.0394380	1.43192550	12.8560190
<i>T-nonlinear</i>	2.13536700	17.1612740	1.35329470	10.2419710
<i>T-bot</i>	0.37721112	3.0211182	0.28054956	2.0564208
<i>TM1</i>	0.56289625	2.4726080	0.65022000	8.5783380
<i>TM2</i>	0.31648500	1.7962474	0.30199860	2.8126283
<i>TM3</i>	1.15259590	5.3824220	0.36903074	1.6285741
<i>I1-1</i>	0.35322627	3.0845199	0.24536760	2.1074777
<i>I1-2</i>	0.38468698	3.6339493	0.35180047	2.4803240
<i>I1-3</i>	0.30614700	2.5460430	0.24242292	1.9377272
<i>I1-4</i>	0.30588250	2.3246558	0.24281265	2.1525698
<i>I1-5</i>	0.33366418	2.0609448	0.28760797	3.4277070
<i>I1-6</i>	0.30224845	1.7820654	0.20792589	1.5811069
<i>I2-1</i>	0.34150276	2.4921500	0.32629030	2.8890820
<i>I2-2</i>	0.31135368	1.7852107	0.24282907	2.4637530
<i>I2-3</i>	0.35905495	2.8148563	0.25670642	2.3792675
<i>I2-4</i>	0.32227376	2.7766125	0.23127094	1.7845937
<i>I2-5</i>	0.30711270	2.3601599	0.19894058	1.4396828
<i>I2-6</i>	0.28511740	2.3259158	0.19201125	1.4109217
<i>I3-1</i>	0.36472487	2.7185680	0.21796600	1.5064819
<i>I3-2</i>	0.33573255	2.4126415	0.24210289	2.1346107
<i>I3-3</i>	0.26717153	1.5455226	0.25082460	1.6653341
<i>I3-4</i>	0.36790776	3.5143754	0.37196410	2.6980913
<i>I3-5</i>	0.35992740	2.4058177	0.32797354	3.1356711
<i>I3-6</i>	0.45859572	3.6622164	0.20298074	1.6304903
<i>PM1</i>	0.69095355	4.3836140	1.12738340	14.991370
<i>PM2</i>	0.76150850	4.2025466	0.41941770	3.5418112
<i>PM3</i>	0.79561660	4.7225520	0.61785805	3.5446390
<i>PB1</i>	0.69200030	4.0209620	0.42884672	3.0700994
<i>PB2</i>	0.67983735	4.8049580	0.41028178	3.4015010
<i>PB3</i>	0.65071950	3.8518867	0.39021996	2.2565530
<i>PB4</i>	0.57293430	3.2341430	0.42279145	3.0852215
<i>P1</i>	0.34426922	3.0211587	0.27629068	2.0682454
<i>P2</i>	0.29241088	2.2792852	0.24325553	1.3644630

<i>P3</i>	0.31247887	1.8916565	0.24532057	1.6781352
<i>P4</i>	0.38857272	3.0215952	0.27944810	2.2310135
<i>P5</i>	0.31763303	2.5104460	0.29194766	2.5090046
<i>P6</i>	0.33388945	2.3694046	0.18980652	1.6118526
<i>P7</i>	0.40847751	2.7208260	0.35844755	1.5627985
<i>P8</i>	0.39311240	2.6294850	0.2994433	3.1214464
<i>P9</i>	0.29907992	2.9477208	0.35012504	3.5816400
<i>P10</i>	0.32220122	1.9993650	0.30104136	2.3180492
<i>P11</i>	0.36420550	2.1221972	0.25071907	1.9728230
<i>P12</i>	0.42473093	2.6068401	0.25088778	1.6395134

It can be observed from Table 5.3 that the average errors and the maximum errors are within acceptable limit (average error $\leq 5\%$ and the maximum errors $\leq 15\%$) with the exceptions that the maximum errors are high for *T-linear* and *T-nonlinear* with back propagation training. These high errors have occurred only for very few samples (maximum 3-4) as compared to the total number of 1500 samples as shown in Figure 5.4 (a) and Figure 5.4 (b) for the outputs T-linear and T-nonlinear respectively. Figure 5.5 (a) and Figure 5.5 (b) show the test plots for T-linear vs. sample number and T-nonlinear vs. sample number with back propagation and conjugate gradient training method respectively for three-layer perceptrons network.

Figure 5.4 (a): Percentage Error of GaN-4 Neural Model with Three-Layer Perceptrons for T-linear Using Back Propagation Training

Figure 5.4 (b): Percentage Error of GaN-4 Neural Model with Three-Layer Perceptrons for T-nonlinear Using Back Propagation Training

Figure 5.5 (a): Neural Model Output vs. Test Data for T-linear Using Three-Layer GaN-4 Model with Back Propagation Training

Figure 5.5 (b): Neural Model Output vs. Test Data for T-nonlinear using Three-Layer GaN-4 Model with Conjugate Gradient Training

Figures 5.5 (a) and (b) show how well the neural model predicts the output using the unseen test data except for the very few samples where the large error occurred.

Figure 5.6 (a): T-nonlinear and I1-1 (Outputs) vs. Power (Input) w.r.t. Bot (Input) for Three-Layer GaN-4 Model with Back Propagation Training

Figure 5.6 (b): TM1 and TM3 (Outputs) vs. Power (Input) w.r.t. Bot (Input) for Three-Layer GaN-4 Model with Conjugate Gradient Training

Figure 5.6 shows the output vs. input plot for this model. The testing errors for four-layer perceptrons network for GaN model are shown in Table B.1.1 in Appendix B. As mentioned earlier, the four-layer perceptrons network has not been well trained for this model. Consequently, the average and maximum errors are comparatively high for some of the outputs of GaN model with four-layer perceptrons as shown in Table B.1.1 in Appendix B.

5.2.3 Training of GaN Model with Five-Port Configuration

The GaN model with five-port configuration has been trained in four ways as follows:

- 1) Three-layer perceptrons network with back propagation training method.
- 2) Three-layer perceptrons network with conjugate gradient training method.
- 3) Four-layer perceptrons network with back propagation training method.
- 4) Four-layer perceptrons network with conjugate gradient training method.

Table 5.4 shows the training errors for GaN model with five-port configuration.

Table 5.4: Training Errors of GaN Model with Five-Port Configuration

Layer/ Training	Hidden Neurons	Initial Condition	Initial Training Error (After 1 st Training)	Final Training Error (After 10 th Training)
3 layer BP	24	max. number of epochs: 100 learning rate: 0.001 momentum factor: 0	0.003643798 at 100 epochs	0.003072574 at 911 epochs
3 layer CG	24	max. number of epochs: 200 function error tolerance: $1e^{-4}$ model parameter tolerance: $1e^{-4}$	0.003507970 at 179 epochs	0.003497720 at 188 epochs
4 layer BP	layer1: 5 layer2: 3	max. number of epochs: 200 learning rate: 0.001 momentum factor: 0	0.019041700 at 200 epochs	0.018975600 at 440 epochs
4 layer CG	layer1: 5 layer2: 3	max. number of epochs: 200 function error tolerance: $1e^{-4}$ model parameter tolerance: $1e^{-4}$	0.022101500 at 154 epochs	0.022080200 at 167 epochs

In Table 5.4, the number of hidden neurons and the initial conditions of the trainings have been automatically selected by the *Neuromodeler*. Figure 5.7 shows the training error of GaN model with five port configuration against the first 500 epochs.

Figure 5.7: Training Error of GaN Model with Five-Port Configuration for Different Training Methods and Structures

It has been observed from Figure 5.7 that the training error is less for three-layer perceptrons network than that of four-layer perceptrons network for GaN model with five-port configuration.

5.2.4 Testing of GaN Model with Five-Port Configuration

Once the neural network was built with the training data, the performance of the network has been tested with a separate set (unseen) of testing data. Table 5.5 shows the training and testing results for GaN model with five-port configuration.

Table 5.5: Training and Testing Results of GaN Model with Five-Port Configuration

Result Training	Epochs	Training Error	Average Testing Error	Maximum Testing Error	Correlation Coefficient
<i>3-layer BP</i>	911	0.003072574	3.2704945	55.065636	0.99974900
<i>4-layer BP</i>	188	0.018975600	3.1327780	54.490158	0.99977285
<i>3-layer CG</i>	440	0.003497720	3.2883837	55.598335	0.99974716
<i>4-layer CG</i>	167	0.022080200	2.8269913	54.724945	0.99984290

It should be mentioned here that the GaN model with five-port configuration was not the optimal choice compared to the four-port configuration as indicated by the simulations performed in chapter 4. Also, it can be seen from these results that it is difficult to train the five-port model effectively. The average error is satisfactory; however, the maximum error is large for all cases. It appears that the five-port model is not only poor from the point of view of a sub-model definition, but also difficult to train.

Table 5.6 shows the average and maximum testing errors for each of the outputs for GaN model with three-layer perceptrons. It has been observed from Table 5.6 that the average errors and the maximum errors are within acceptable limit (average error $\leq 5\%$ and the maximum errors $\leq 15\%$) for all the outputs except TP1-TP5 (port heat-flows) for both back propagation and conjugate gradient training method. These large errors in the heat flows will produce subsequent errors in the solution of any mixed model using this sub-model and is most likely not suitable for use.

Table 5.6: Testing Errors of GaN Model with Three-Layer Perceptrons and Five-Port Configuration

Output	Average Error (BP3)	Maximum Error (BP3)	Average Error (CG3)	Maximum Error (CG3)
<i>T-linear</i>	2.15972850	9.2298290	2.27445770	8.9718740
<i>T-nonlinear</i>	2.29811550	8.5067260	2.44497630	7.2865090
<i>TP1</i>	15.23984050	44.3611530	15.33548200	43.9338230
<i>TP2</i>	16.52241500	54.4600260	16.57920500	53.6577840
<i>TP3</i>	17.26269700	53.3757100	17.33597200	53.7503000
<i>TP4</i>	17.49096900	55.0656360	17.52365900	55.5983400
<i>TP5</i>	16.28382000	50.3527070	16.34496700	50.194145
<i>I1-1</i>	1.71833410	5.5231786	1.74308370	5.7716880
<i>I1-2</i>	1.54450420	6.0625873	1.56144010	5.5460080
<i>I1-3</i>	1.76036400	6.0031247	1.73555390	5.4702454
<i>I1-4</i>	1.23968570	4.2949850	1.23476820	3.8861756
<i>I1-5</i>	1.15433180	4.1855726	1.11744630	3.9670910
<i>I1-6</i>	1.24651730	4.2173047	1.22332530	4.2373657
<i>I2-1</i>	0.65629643	2.3617470	0.65853570	2.2760172
<i>I2-2</i>	0.56176406	2.1727622	0.56966037	2.0520031
<i>I2-3</i>	0.69446295	2.3387194	0.67227900	2.6447906
<i>I2-4</i>	0.77190690	2.4907439	0.78747670	2.5137987
<i>I2-5</i>	0.42996117	1.5726722	0.41901140	1.6350898
<i>I2-6</i>	0.87606610	3.1509798	0.87778090	3.2556517
<i>I3-1</i>	1.26314970	4.0477138	1.27031980	4.0095960
<i>I3-2</i>	0.87014280	2.7609124	0.88129980	2.9948459
<i>I3-3</i>	1.37538710	4.4899206	1.38266060	4.5289536
<i>I3-4</i>	1.62167110	5.2506433	1.63457290	4.9991810
<i>I3-5</i>	1.17188400	3.7345264	1.19902150	3.8026898
<i>I3-6</i>	1.75507040	5.4527493	1.77278850	5.7172300
<i>PM1</i>	2.82873400	8.6010130	2.85109040	9.0241970
<i>PM2</i>	3.35487600	9.7400840	3.38093350	9.4547760
<i>PM3</i>	3.91800380	11.4465820	3.94236700	11.1299340
<i>PB1</i>	2.91111970	8.7053950	2.90949800	8.5569935
<i>PB2</i>	3.02547740	9.0862060	3.03168230	9.1865280
<i>PB3</i>	2.99874780	9.1148405	3.02561140	9.0056270
<i>PB4</i>	3.37262060	9.3556150	3.38295220	9.7333100
<i>P1</i>	1.56043670	5.8935120	1.55252500	5.4855480
<i>P2</i>	1.16651950	4.3430867	1.13764100	3.8920557
<i>P3</i>	0.57099026	2.2641394	0.56479000	2.1393354
<i>P4</i>	0.44566480	1.5894451	0.45877773	1.6813142
<i>P5</i>	0.87627960	2.6808000	0.88039255	2.9385588
<i>P6</i>	1.18873140	3.6988410	1.20522210	3.8243818
<i>P7</i>	1.75840300	5.5204870	1.74836130	5.2982388
<i>P8</i>	1.23599370	3.9630525	1.22817720	3.9857590
<i>P9</i>	0.69552430	2.5355825	0.70698017	2.5374393
<i>P10</i>	0.90821780	3.1399927	0.92098075	3.2287571
<i>P11</i>	1.38333690	4.5021550	1.40505080	4.5511312
<i>P12</i>	1.73299200	5.4227520	1.77610460	5.7185626

Figure 5.8 shows the testing error plot for TP1 for GaN model with three-layer perceptrons network.

Figure 5.8: Percentage Error of Neural Model for TP1 Using Three-Layer GaN-5 Model with Back Propagation Training

The output vs. input plots for this model are shown in Figure 5.9 (a) and Figure 5.9 (b). These two figures indicate the non-linearity present in the model. The testing errors for four-layer perceptrons network are shown in Table B.1.2 in Appendix B. As mentioned earlier, the four-layer perceptrons network has not been well trained for this model. Consequently, the average and maximum errors are comparatively high for some of the outputs of GaN model with four-layer perceptrons as shown in Table B.1.2 in Appendix B.

Figure 5.9 (a): TP1 and TP5 (Outputs) vs. Port1 (Input) w.r.t Port5 (Input) for Three-Layer GaN-5 Model with Back Propagation Training

Figure 5.9 (b): T-linear and T-nonlinear (Outputs) vs. Port1 (Input) w.r.t Port5 (Input) for Three-Layer GaN-5 Model with Conjugate Gradient Training

5.3 GaAs Based Power Amplifier

As mentioned in Chapter 4, the five-port configuration has been selected as the appropriate choice for neural network modeling for GaAs based power amplifier model. The inputs for the neural network model have been varied as follows: port1 (port at the bottom) temperature has been varied from 300 – 330K (with an increase of 15K), port2 to port5 (four metal ports) temperatures have been varied from 300 – 345K (with an increase of 15K) and power has been varied from 0 – 0.01W (with an increase of 0.0025W). The outputs of this model include the maximum temperature (T_{linear}) of a simple linear solution of the model, maximum temperature ($T_{nonlinear}$) of a non-linear solution, port heat-flows ($TP1-TP5$) for each of the input ports and temperatures at 21 different points that might be of interest. A total of 3840 data (where each data represents a set of all the inputs and outputs) have been generated for training. The performance of the trained model has been evaluated by a total of 1500 data.

5.3.1 Training of GaAs Based Power Amplifier

The model has been trained in four different ways as follows:

- 1) Three-layer perceptrons network with back propagation training method.
- 2) Three-layer perceptrons network with conjugate gradient training method.
- 3) Four-layer perceptrons network with back propagation training method.
- 4) Four-layer perceptrons network with conjugate gradient training method.

Table 5.7 shows the summary of training errors for GaAs model. In this table, the number of hidden neurons and the initial conditions of the trainings have been automatically selected by the *Neuromodeler*.

Table 5.7: Training Errors of GaAs Model

Layer/ Training	Hidden Neurons	Initial Condition	Initial Training Error (After 1 st Training)	Final Training Error (After 10 th Training)
3 layer BP	24	max. number of epochs: 100 learning rate: 0.001 momentum factor: 0	0.01096288 at 100 epochs	0.005339213 at 1000 epochs
3 layer CG	24	max. number of epochs: 200 function error tolerance: $1e^{-4}$ model parameter tolerance: $1e^{-4}$	0.00494035 at 100 epochs	0.004048710 at 413 epochs
4 layer BP	layer1: 5 layer2: 3	max. number of epochs: 200 learning rate: 0.25 momentum factor: 0	0.06864810 at 200 epochs	0.065361600 at 817 epochs
4 layer CG	layer1: 5 layer2: 3	max. number of epochs: 200 function error tolerance: $1e^{-4}$ model parameter tolerance: $1e^{-4}$	0.10534600 at 58 epochs	0.070714500 at 150 epochs

Figure 5.10 shows the training error against the first 500 epochs.

Figure 5.10: Training Error of GaAs Model with Five-Port Configuration for Different Training Methods and Structures

It has been observed from Figure 5.10 that at any epoch, the training error is less for three-layer perceptrons network than that of four-layer perceptrons network.

5.3.2 Testing of GaAs Based Power Amplifier

Once the neural network was built with the training data, the performance of the network has been tested with a separate set (unseen) of testing data. Table 5.8 shows the training and testing results for GaAs model with five-port configuration.

Table 5.8: Training and Testing Results for GaAs Model

Result Training	Epochs	Training Error	Average Testing Error	Maximum Testing Error	Correlation Coefficient
<i>3-layer BP</i>	1000	0.005339213	0.5503954	13.041626	0.99999386
<i>4-layer BP</i>	413	0.065361600	5.1452947	55.120190	0.99990220
<i>3-layer CG</i>	817	0.004048710	0.5462286	13.099299	0.99999547
<i>4-layer CG</i>	150	0.070714500	5.5548210	54.780457	0.99990046

It can be observed from Table 5.8 that the average testing errors and maximum testing errors are less and correlation coefficients are higher for models with three-layer perceptrons network than that of four-layer perceptrons network. Therefore, it can be concluded that the model is well trained with conjugate gradient training as well as back propagation training method for three-layer perceptrons network.

Table 5.9 shows the average and maximum testing errors for each of the outputs for GaAs model with three-layer perceptrons.

Table 5.9: Testing Errors of GaAs Model with Three-Layer Perceptrons

Output	Average Error (BP3)	Maximum Error (BP3)	Average Error (CG3)	Maximum Error (CG3)
<i>T-linear</i>	2.25731470	13.0416360	1.97224880	13.09930000
<i>T-nonlinear</i>	1.79904580	10.6978610	1.45902140	8.94953800
<i>TP1</i>	0.57886840	1.5743921	0.59930650	1.40613060
<i>TP2</i>	0.35232836	1.2966421	0.25267416	0.86466426
<i>TP3</i>	0.35248274	1.1821772	0.20652726	1.48224310
<i>TP4</i>	0.42490458	1.6332222	0.29367290	0.94798980
<i>TP5</i>	0.31927323	1.1493973	0.23900111	0.75720390
<i>I1-1</i>	0.43714833	1.7034156	0.24551924	0.74990773
<i>I1-2</i>	0.40407280	1.4732306	0.29216793	1.00121990
<i>I1-3</i>	0.44717246	1.8181883	0.29090983	1.00294960
<i>I2-1</i>	0.48667547	1.7483943	0.26951233	0.99097687
<i>I2-2</i>	0.46217000	1.5806475	0.32884246	1.09387120
<i>I2-3</i>	0.43428900	1.6779274	0.29080160	1.14267250
<i>I3-1</i>	0.42596188	1.5146278	0.15763140	0.82151645
<i>I3-2</i>	0.37499340	1.1323408	0.37822070	1.47117380
<i>I3-3</i>	0.34860190	1.3983166	0.29815072	1.22873160
<i>I4-1</i>	0.42374230	1.5067503	0.34187130	1.05552090
<i>I4-2</i>	0.42517465	1.6732249	0.29112430	1.01818970
<i>I4-3</i>	0.35762840	1.3381972	0.28807318	0.94420010
<i>PM1</i>	0.50909954	1.9942312	0.36783135	1.27201190
<i>PM2</i>	0.42854570	1.4249014	0.41840208	1.44194270
<i>PM3</i>	0.44432476	1.5516003	0.34155172	1.25239920
<i>PM4</i>	0.40518090	1.4924512	0.39142040	1.39261150
<i>PB1</i>	0.57582060	1.5247957	1.02286890	1.88858410
<i>PB2</i>	0.34980650	1.0355856	1.13225270	2.08211260
<i>PB3</i>	0.47552297	1.4614894	1.12922170	2.20019300
<i>PB4</i>	0.60729500	2.0441377	0.95298970	1.92422180
<i>PB5</i>	0.50362550	1.3863567	1.04258850	2.06928900

It has been observed from Table 5.9 that the average errors as well as the maximum errors are within acceptable limit i.e., average error $\leq 5\%$ and the maximum errors $\leq 15\%$. It can be concluded that the model with three-layer perceptrons network is well trained with back propagation as well as conjugate gradient training method. Figure 5.11 (a) and Figure 5.11 (b) show the testing error plots for T-linear with conjugate gradient and T-nonlinear with back propagation training method respectively for three-layer perceptrons network.

Figure 5.11 (a): Percentage Error of Neural Model for T-linear Using Three-Layer GaAs Model with Conjugate Gradient Training

Figure 5.11 (b): Percentage Error of Neural Model for T-nonlinear Using Three-Layer GaAs Model with Back Propagation Training

Figure 5.12 (a) shows T-nonlinear vs. sample number and Figure 5.12 (b) shows TP1 vs. sample number plots for back propagation and conjugate gradient training method respectively. These plots show how well the neural model predicts the output using the unseen test data.

Figure 5.12 (a): Neural Model Output vs. Test Data for T-nonlinear Using Three-Layer GaAs Model with Back Propagation Training

Figure 5.12 (b): Neural Model Output vs. Test Data for TP1 Using Three-Layer GaAs Model with Conjugate Gradient Training

Figure 5.13 (a) and Figure 5.13 (b) show the output vs. input plot for GaAs model with three-layer perceptrons network. These figures indicate the non-linearity present in the model. The testing errors for four-layer perceptrons network are shown in Table B.2.1 in Appendix B. As mentioned earlier, the four-layer perceptrons network has not been well trained for this model. Consequently, the average and maximum errors are comparatively high for some of the outputs of GaAs model with four-layer perceptrons.

Figure 5.13 (a): T-nonlinear and PM1 (Outputs) vs. Power (Input) w.r.t Port5 (Input) for Three-Layer GaAs Model with Back Propagation Training

Figure 5.13 (b): TP2 and TP5 (Outputs) vs. Port2 (Input) w.r.t Port5 (Input) for Three-Layer GaAs Model with Conjugate Gradient Training

5.4 Package Model

The results obtained from the simulation using *Atar* shows that the three-port configuration gives best results for this model. Accordingly, the inputs chosen for this model for neural network modeling are as follows: the heat-transfer coefficient in the top-side of the model (*alpha-top*), the three port temperatures (*T1*, *T2* and *T3*) and the power. The value of *alpha-top* has been chosen as, $10^{-4} - 10^{-8} \text{W}/\mu\text{m}^2\text{K}$ (with a decrease of $10^{-1} \text{W}/\mu\text{m}^2\text{K}$), using log scale. The temperatures have been varied from 300 – 340K (with an increase of 10K) while the power has been varied as 1.0 – 0W (with a decrease of 0.25W). The outputs of this model include the maximum temperature (*T-linear*) of a simple linear solution of the model, maximum temperature (*T-nonlinear*) of a non-linear solution, port heat-flow (*T-alpha*) due to *alpha*, port heat-flows (*TP1-TP3*) for each of the input ports and temperatures at 16 different points that might be of interest. A total of approximately 3100 data (where each data represents a set of all the inputs and outputs) have been generated for training. The performance of the trained model has been evaluated by a total of 1500 data.

5.4.1 Training of Package Model

The model has been trained in four different ways as follows:

- 1) Three-layer perceptrons network with back propagation training method.
- 2) Three-layer perceptrons network with conjugate gradient training method.
- 3) Four-layer perceptrons network with back propagation training method.

4) Four-layer perceptrons network with conjugate gradient training method.

Table 5.10 shows the summary of training errors for Package model. In this table, the number of hidden neurons and the initial conditions of the trainings have been automatically selected by the *Neuromodeler*. Figure 5.14 shows the training error against the first 300 epochs.

Table 5.10: Training Errors of Package Model

Layer/ Training	Hidden Neurons	Initial Condition	Initial Training Error (After 1 st Training)	Final Training Error (After 10 th Training)
3 layer BP	20	max. number of epochs: 100 learning rate: 0.25 momentum factor: 0	0.007269213 at 100 epochs	0.005346793 at 1000 epochs
3 layer CG	20	max. number of epochs : 200 function error tolerance: $1e^{-4}$ model parameter tolerance: $1e^{-4}$	0.011737000 at 100 epochs	0.006601130 at 619 epochs
4 layer BP	layer1: 5 layer2: 3	max. number of epochs: 200 learning rate: 0.25 momentum factor: 0	0.029792300 at 200 epochs	0.028774800 at 1073 epochs
4 layer CG	layer1: 5 layer2: 3	max. number of epochs: 200 function error tolerance: $1e^{-4}$ model parameter tolerance: $1e^{-4}$	0.053253600 at 44 epochs	0.031112200 at 253 epochs

Figure 5.14: Training Error of Package Model with Three-Port Configuration for Different Training Methods and Structures

It has been observed from Figure 5.14 that the training error is less for three-layer perceptrons network than that of four-layer perceptrons network.

5.4.2 Testing of Package Model

Once the neural network was built with the training data, the performance of the network has been tested with a separate set (unseen) of testing data. Table 5.11 shows the training and testing results for Package model with three-port configuration.

Table 5.11: Training and Testing Results for Package Model

Result Training	Epochs	Training Error	Average Testing Error	Maximum Testing Error	Correlation Coefficient
<i>3-layer BP</i>	1000	0.005346793	0.77947116	8.4207680	0.99999740
<i>4-layer BP</i>	619	0.028774800	2.43547370	26.2361720	0.99997896
<i>3-layer CG</i>	1073	0.006601130	0.87973390	7.1821856	0.99999720
<i>4-layer CG</i>	253	0.031112200	2.78219400	28.0604290	0.99997720

It can be observed from Table 5.11 that the average testing errors and maximum testing errors are also less and correlation coefficients are higher for models with three-layer perceptrons network than that of four-layer perceptrons network. Therefore, it can be concluded that the model is well trained with conjugate gradient training as well as back propagation training method for three-layer perceptrons network.

Table 5.12 shows the average and maximum testing errors for each of the outputs for Package model with three-layer perceptrons.

Table 5.12: Testing Errors of Package Model with Three-Layer Perceptrons

Output	Average Error (BP3)	Maximum Error (BP3)	Average Error (CG3)	Maximum Error (CG3)
<i>T-linear</i>	1.9079660	8.4207680	1.93973600	7.1821860
<i>T-nonlinear</i>	1.8602020	8.2069160	1.90911300	6.8886860
<i>T-alpha</i>	0.7539850	3.2350280	0.79211800	3.6257580
<i>TP1</i>	0.3346260	1.3696930	0.47170900	2.3380610
<i>TP2</i>	0.2442880	1.0371920	0.29170700	1.3782190
<i>TP3</i>	0.2092270	0.9276220	0.72241200	2.4142770
<i>P1</i>	0.8534630	3.1891340	0.91875100	3.8479100
<i>P2</i>	0.7514180	2.9953560	0.84681100	3.6422400
<i>P3</i>	0.7514570	2.9783900	0.82102900	3.5877600
<i>P4</i>	0.8524760	3.1908970	0.91211900	3.9821170
<i>P5</i>	0.7510680	2.9737030	0.82699600	3.5480050
<i>P6</i>	0.6039650	2.4038430	0.71510000	3.3758670
<i>P7</i>	0.6021840	2.3595240	0.70264400	3.3025030
<i>P8</i>	0.7507870	2.9217370	0.83774900	3.6670860
<i>P9</i>	0.7519390	2.9984000	0.83870500	3.5670450
<i>P10</i>	0.6042490	2.3940230	0.71061200	3.6161170
<i>P11</i>	0.6049410	2.4063890	0.73473200	3.4141590
<i>P12</i>	0.7543090	2.9893530	0.83378000	3.6477950
<i>P13</i>	0.8493498	3.2149713	0.90250870	3.8633716
<i>P14</i>	0.7538413	3.0412900	0.87024546	3.7181478
<i>P15</i>	0.7522054	3.0022050	0.83813760	3.5829217
<i>P16</i>	0.8504185	3.2247367	0.91743120	4.0959105

It has been observed from Table 5.12 that the average errors as well as the maximum errors are within acceptable limit i.e., average error $\leq 5\%$ and the maximum errors $\leq 15\%$. It can be concluded that the model with three-layer perceptrons network is well trained with back propagation as well as conjugate gradient training method. Figure 5.15 shows the testing error plot for T-nonlinear with conjugate gradient training.

Figure 5.15: Percentage Error of Neural Model for T-nonlinear Using Three-Layer Package Model with Conjugate Gradient Training

Figure 5.16 shows the plot for T-nonlinear vs. sample number and Figure 5.17 shows the output vs. input plot.

Figure 5.16: Neural Model Output vs. Test Data for T-nonlinear Using Three-Layer Package Model with Back Propagation Training

Figure 5.17 (a): T-nonlinear and P16 (Outputs) vs. Alpha-top (Input) w.r.t T1 (Input) for Three-Layer Package Model with Back Propagation Training

Figure 5.17 (b): T-alpha and TP1 (Outputs) vs. Alpha-top (Input) w.r.t T1 (Input) for Three-Layer Package Model with Back Propagation Training

Figure 5.17 (a) and Figure 5.17 (b) clearly indicate the non-linearity present in the model. The testing errors for four-layer perceptrons network are shown in Table B.3.1 in Appendix B. As mentioned earlier, the four-layer perceptrons network has not been well trained for this model. Consequently, the average and maximum errors are comparatively high for some of the outputs of Package model with four-layer perceptrons.

5.5 Summary

Neural network model have been built for all the three package models. The results obtained from neural network modeling show that the models with three-layer perceptrons have been trained well. But the four-layer perceptrons did not train well. The average testing errors for three-layer perceptrons network are: 0.5% (four-port GaN model with BP), 0.38% (four-port GaN model with CG), 0.55% (GaAs model with BP), 0.54% (GaAs model with CG), 0.78% (Package model with BP) and 0.88% (Package model with CG). These small errors indicate that neural networks can be utilized to build non-linear thermal models with sufficient accuracy. In the next chapter, the use of sub-model to determine the thermal behavior of a detailed model is presented.

Chapter 6

Use of Neural Networks Models in Thermal Simulation

This chapter shows how the sub-modeling approach is used to determine the overall thermal behavior of a mixed-model consisting of a detailed model and non-linear sub-models based on using a neural network approach. It then presents the comparison between the temperatures of a fully detailed model and a mixed-model for the three package models mentioned earlier.

6.1 Use of Neural Networks Sub-models in Mixed Model

As seen from Chapter 5, neural network sub-models have been built by training the models with a set of training data for each model. A fully detailed model can be broken into a base-model and a number of sub-models. To determine the thermal behavior of the mixed-model one needs to solve for the temperatures in the detailed base-model with attached sub-models. This method should be fast, accurate and should be able to represent all the temperatures in the base and the port temperatures and temperatures of interest of the sub-model. The set of equations which describe this problem are non-linear

due to the non-linear neural network sub-models. The solution of this set of equations can be obtained in an iterative way by using the MATLAB/C code – representing the input-output relationships of the thermal sub-model – that is possible to generate using *Neuromodeler*. Maximum temperature of each sub-model as well as temperatures at different points of interest can be determined through this iteration process. It is worthwhile to mention that the training and testing errors were less when the neural network had been based on three-layer perceptrons, as observed in Chapter 5. Consequently, the MATLAB/C code obtained from three-layer perceptrons network has been utilized in this chapter for calculating the temperatures of the sub-model.

Various issues are involved in calculating the temperatures in this iterative way. Convergence is one of the major issues. The iteration process continues until the convergence criterion is met. In this thesis, the convergence is chosen as $1e^{-5}$ K. Another concern is the initial port temperatures used at the start of the iteration. In order to determine the port heat-flows and output temperatures (T-max and other temperatures of interest) the input port temperatures (initial guess for the iteration) should be chosen such that the iteration converges. These initial port temperatures can be easily selected in two obvious ways: these temperatures can either be taken as 300K or they can be obtained from a solution of the linear mixed-model comprised of the base-model (which is linear) and linear sub-models generated using *Atar*. It has been observed that if the initial guess for port temperature is selected as 300K, it does not provide consistent convergence. Consequently, the initial guess for port temperature for the iteration has been taken from linear solution, which provides a much closer approximation to the actual port

temperatures of the non-linear problem. Another issue that relates to the convergence of the solution is the calculation of the “new” port temperatures at the end of each iteration. These temperatures can easily be extracted from the new base-model temperatures; however, it has been found that for robust convergence it was needed to average them with the previous iterations values. The formula used to do this is:

$$T_p = \frac{T_{p_{new}} + \alpha \times T_{p_{old}}}{1 + \alpha} \quad (6.1)$$

where, α determines the degree of averaging. For $\alpha = 0$ we have simple iteration and for α greater than one we have a specified degree of averaging. A trade-off will exist between number of iterations to convergence and robustness of the algorithm.

The pseudo code for determining the output temperatures in the above-mentioned iterative process is provided at the end of this section. After calculating the maximum temperatures and temperatures at different points of interest, errors have been calculated using Equation (6.2) for temperatures of each sub-model with respect to the temperatures of the detailed model.

$$Error = \frac{|T_{det} - T_{sub}|}{T_{det} - 300} \quad (6.2)$$

where, T_{det} is the temperature at a point of interest in the fully detailed model and T_{sub} is the corresponding temperature of the sub-model.

Pseudo Code:

```

num_sub = N; % Number of sub-models
alpha = 2; % Averaging rate of  $T_p$ 
num_iteration = 100; % Number of iterations
conv = 1e-5; % Convergence
delta_T(1) = 10; % Initial value for delta_T – very large
Tp = Tp_Lin0; % Initial value from the linear solution using
% Atar
Read (B, Fb); % For calculating
%  $B \times T_s = F_b + L_1 I_{p_1} + L_2 I_{p_2} + \dots$ 

for i = 1 to num_sub % For each sub-model,
    Read (Li); % Linking matrices for each sub-model
End

[L,U] = LU_factorization(B);

for j = 1 to num_iteration % Start iteration,

    for i = 1 to num_sub % Get outputs from Neural Model
        input = [Tp, Power];
        [Tmax, Ip, Tj] = Neuromod_function(input);
    end

    F = Fb % Boundary conditions on base-model

    for i = 1 to num_sub % For each sub-model,
        F = Fb + L*Ip; % Add in port heat-flows
    end

    T = U\L\F; % Solve for new base-model temperatures
    Tmax(j) = max(T); % Tmax for jth iteration

    If j >= 2 % Calculate maximum delta_T
        delta_T(j) = max (abs (Tmax(j) - Tmax(j-1)))
    end;

    if delta_T(j) <= conv % Check Convergence
        write ('converged in jth iteration');
        break;
    end

    for i = 1 to num_sub % For each sub-model
        Tp_old = Tp; % Calculate new Tp
        Tp_new = Li' * T
        Tp = (Tp_new + alpha * Tp_old) / (1 + alpha)
    end

end
end

```


6.2 Full Models Obtained from Neural Networks Sub-models

This section presents the temperature prediction at different points of interest for sub-models as well as detailed model for the three models mentioned earlier. It then calculates the errors for temperatures of the sub-models with respect to that of the detailed model.

6.2.1 GaN Based Power Package Amplifier

A detailed model of a GaN amplifier has been represented by eight sub-models. Figure 6.1 (a) and Figure 6.1 (b) show the layouts of the GaN sub-model and the amplifier. Figure 6.2 shows a view of the fully detailed *Atar* model of the amplifier. Details of the GaN sub-model attachment and a fully detailed model can be seen in Figure 6.3. The GaN amplifier had a fixed 300K BC applied to the bottom of the model.

Table 6.1 and Table 6.2 show the temperatures at different points of interest for a detailed model and two sub-models and corresponding errors for GaN model with four-port configuration and five-port configuration respectively. The output temperatures for this model have been calculated at the point where the maximum temperature is reached and also at three points of each of the fingers of GaN, i.e., a total of eighteen points.

(a)

(b)

Figure 6.1 (a): GaN Sub-model Layout

Figure 6.1 (b): GaN Mixed-model Layout

Figure 6.2: Detailed GaN Model

Figure 6.3 (a): Details of GaN Sub-model Placement

Figure 6.3 (b): GaN Full-model Showing GaN Amplifier Detail

Figure 6.4: (a) Temperature of Detailed GaN Model (b) Details View of Temperature of Fully Detailed GaN Model (c) Temperature of GaN Base-model Using Sub-model

Figure 6.4 (a) shows the temperature profile of a detailed GaN model. Figure 6.4 (b) shows the same model in detail and presents one of the individual power cells. It has been observed that the temperature is higher (appearing as red) in the centre, which of course is where the power is created. Figure 6.4 (c) shows the temperature of the GaN base-model obtained using a mixed-model with attached sub-models. It has been observed from this figure that the model achieves the maximum temperature (appearing as red) in the centre of the sub-model.

Table 6.1: Output Temperatures for Detailed and Sub-models and Corresponding Errors of GaN Model with Four-Port Configuration for Back-side BC

Output	Model-1			Model-2		
	T _{full} (K)	T _{sub} (K)	Error	T _{full} (K)	T _{sub} (K)	Error
<i>T-max</i>	398.317029	399.7594	0.014671	400.581279	402.3671	0.017755
<i>I1-1</i>	372.991361	371.4121	0.021636	375.434600	373.5863	0.024502
<i>I1-2</i>	377.110713	378.4875	0.017855	379.590885	380.7268	0.014272
<i>I1-3</i>	373.440987	372.4964	0.012862	375.848452	374.7434	0.014569
<i>I1-4</i>	373.227389	374.8620	0.022322	375.582251	377.1359	0.020556
<i>I1-5</i>	378.850890	383.4079	0.057793	381.250747	385.7992	0.055980
<i>I1-6</i>	374.102257	376.2137	0.028494	376.413743	378.4872	0.027135
<i>I2-1</i>	378.764022	375.7625	0.038108	377.167597	378.0198	0.011044
<i>I2-2</i>	384.936679	385.2393	0.003563	383.497458	387.6618	0.049874
<i>I2-3</i>	379.409432	377.1021	0.029056	378.032018	379.2414	0.015499
<i>I2-4</i>	375.397708	376.7933	0.018510	377.572127	379.0214	0.018683
<i>I2-5</i>	381.747531	383.3897	0.020088	383.967451	385.7068	0.020715
<i>I2-6</i>	376.392262	377.1110	0.009409	378.519608	379.2982	0.009916
<i>I3-1</i>	374.767556	375.6170	0.011361	380.633531	377.8369	0.034683
<i>I3-2</i>	380.641508	383.8801	0.040160	386.374110	386.1167	0.002980
<i>I3-3</i>	375.686582	377.1087	0.018790	381.246595	379.4082	0.022627
<i>I3-4</i>	375.628724	373.6995	0.025509	377.698770	375.8596	0.023671
<i>I3-5</i>	380.179454	377.7390	0.030437	382.265884	380.0177	0.027328
<i>I3-6</i>	375.892896	373.2756	0.034487	377.919380	375.3908	0.032451

Table 6.2: Output Temperatures for Detailed and Sub-models and Corresponding Errors of GaN Model with Five-Port Configuration for Back-side BC

Output	Model-1			Model-2		
	T _{full}	T _{sub}	Error	T _{full}	T _{sub}	Error
	(K)	(K)		(K)	(K)	
<i>T-max</i>	398.317029	402.2699	0.040205	400.581279	404.8189	0.042131
<i>I1-1</i>	372.991361	371.4787	0.020724	375.434600	374.2894	0.015181
<i>I1-2</i>	377.110713	378.6016	0.019334	379.590885	381.4354	0.023175
<i>I1-3</i>	373.440987	373.0715	0.005031	375.848452	376.1865	0.004457
<i>I1-4</i>	373.227389	376.0694	0.038811	375.582251	379.0280	0.045589
<i>I1-5</i>	378.850890	384.0103	0.065432	381.250747	387.0473	0.071342
<i>I1-6</i>	374.102257	377.1412	0.041010	376.413743	380.0923	0.048140
<i>I2-1</i>	378.764022	376.9989	0.022410	377.167597	380.0065	0.036789
<i>I2-2</i>	384.936679	385.8146	0.010336	383.497458	388.7163	0.062503
<i>I2-3</i>	379.409432	378.5420	0.010924	378.032018	381.4978	0.044415
<i>I2-4</i>	375.397708	377.8957	0.033131	377.572127	380.7261	0.040659
<i>I2-5</i>	381.747531	384.3663	0.032035	383.967451	387.1374	0.037752
<i>I2-6</i>	376.392262	377.6136	0.015988	378.519608	380.3876	0.023790
<i>I3-1</i>	374.767556	376.9795	0.029584	380.633531	379.8680	0.009494
<i>I3-2</i>	380.641508	384.8099	0.051690	386.374110	387.5195	0.013261
<i>I3-3</i>	375.686582	378.2054	0.033280	381.246595	380.9507	0.003642
<i>I3-4</i>	375.628724	375.3584	0.003574	377.698770	378.1030	0.005203
<i>I3-5</i>	380.179454	379.3287	0.010611	382.265884	382.0114	0.003093
<i>I3-6</i>	375.892896	375.0958	0.010503	377.919380	377.8878	0.000405

The results for other sub-models are shown in Table C.1.1 to Table C.1.3 (for four-port configuration) and in Table C.1.4 to Table C.1.6 (for five-port configuration) of Appendix C. It can be observed that the errors are small ($\leq 7\%$ and $\leq 8\%$ for four-port and five-port configuration respectively) when the detailed model is represented by a sub-model with four-port and five-port configurations.

Figure 6.5 (a) and Figure 6.5 (b) show the temperature error of GaN sub-model with four-port configuration and Figure 6.5 (c) shows the temperature error of the same model with five-port configuration. It has been observed from these figures that the temperature error is higher (appearing as red) in the centre of the sub-model for four-port configuration and

for five-port configuration temperature error is higher (appearing as red) in the centre and also in one of the metal ports. It can be observed that the temperature error for the majority of the structure is very small and the error is concentrated at the ports where a constant temperature is imposed on a region of the base-model.

Table 6.3 shows the temperature rise and maximum error for linear and non-linear substrate simulations.

Table 6.3: Temperature Rise and Maximum Error for Linear and Non-linear Substrate of GaN Model

Port	Substrate	Absolute Error (K)	Maximum Error (%)
4-port	linear	3.44	7.50
4-port	non-linear	4.09	8.50
5-port	linear	6.50	13.8
5-port	non-linear	6.40	13.3

It has been observed from Table 6.3 that when a mixed-model is used with a particular port configuration introduced for a sub-model, there is a temperature error created by the imposition of a uniform temperature over a port. Table 6.3 shows that for a four-port configuration, the temperature rise and error are more for non-linear sub-model than that of linear sub-model. For five-port configuration, the error is actually less for non-linear sub-model than that of linear sub-model. These temperature errors are within satisfactory limit. The errors presented here indicate that the primary source of error is not due to the use of a non-linear sub-model but just due to the use of sub-models and the port-configuration selected.

**Figure 6.5: (a) Temperature Error of GaN Sub-model with Four-Port Configuration
 (b) Detailed View of Temperature Error for Four-Port Configuration
 (c) Temperature Error of GaN Sub-model with Five-Port Configuration**

6.2.2 GaAs Based Power Amplifier

The mixed-model of a GaAs power amplifier has been built using ten sub-models with five-port configuration. A detailed thermal model of the GaAs power amplifier die with a five-section cascade gain cell structure is shown in Figure 6.6 (a). A fully detailed model of the amplifier is shown in Figure 6.6 (b).

The output temperatures have been calculated at the point where the maximum temperature of the model is reached and also at three different points at each of the four fingers, i.e., a total of twelve points. Table 6.4 shows the temperatures at different points of interest for both detailed and two sub-models and corresponding errors for GaAs model with five-port configuration with a fixed 300K BC applied to the back-side of the model.

Table 6.4: Output Temperatures for Detailed and Sub-models and Corresponding Errors of GaAs Model with Back-side BC

Output	Model-1			Model-2		
	T _{full}	T _{sub}	Error	T _{full}	T _{sub}	Error
	(K)	(K)		(K)	(K)	
<i>T-max</i>	460.618249	461.6152	0.006207	466.532133	466.9409	0.002455
<i>I1-1</i>	397.865100	395.0147	0.029126	399.651200	398.5926	0.010623
<i>I1-2</i>	459.851800	459.1584	0.004338	466.111600	463.6721	0.014686
<i>I1-3</i>	448.709700	446.8892	0.012242	451.209200	451.1796	0.000196
<i>I2-1</i>	398.886600	397.4286	0.014744	401.503600	401.0870	0.004104
<i>I2-2</i>	464.764800	462.0909	0.016229	467.108200	466.4999	0.003640
<i>I2-3</i>	451.816500	449.5302	0.015060	454.499600	453.9034	0.003859
<i>I3-1</i>	399.190300	397.8209	0.013806	403.244600	401.4333	0.017544
<i>I3-2</i>	463.214700	463.1592	0.000340	468.350500	467.5339	0.004851
<i>I3-3</i>	452.749400	450.2851	0.016133	455.253400	454.6569	0.003842
<i>I4-1</i>	395.936300	394.6022	0.013906	398.306300	398.2605	0.000466
<i>I4-2</i>	459.293100	457.4468	0.011591	464.134900	461.8946	0.013649
<i>I4-3</i>	448.735600	446.3598	0.015973	451.905500	450.5702	0.008790

The results for other sub-models are shown in Table C.2.1 to Table C.2.4 of Appendix C. It can be observed that the errors are small (within 3%) when the mixed-model is represented by the sub-models with five-port configuration.

Figure 6.7 (a) shows the temperature of a GaAs model for ten sub-models. It has been observed from the figure that the temperature is higher (appearing as red) in the centre of the sub-model. Figure 6.7 (b) shows the detailed view of temperature in the sub-model. Figure 6.7 (c) shows the temperature error (appearing as red) in the substrate of the GaAs model. The error is clearly concentrated around the regions where the ports of the sub-models are attached to the base-model.

Table 6.5 shows the temperature rise and maximum error for linear and non-linear substrate.

Table 6.5: Temperature Rise and Maximum Error for Linear and Non-linear Substrate of GaAs Model

Substrate	Absolute Error (K)	Maximum Error (%)
<i>Linear</i>	2.06	7.20
<i>Non-linear</i>	3.06	10.33

It has been observed from Table 6.5 that the primary source of error in temperature is due to the port-configuration and port-selection of the sub-model. The error for a non-linear sub-model is only slightly higher than that of the linear sub-model indicating the primary source of error is due to the use of sub-models.

Figure 6.6 (a): GaAs Model

Figure 6.6 (b): Detail GaAs Model

(a)

(b)

(c)

Figure 6.7: (a) Top View of Temperature of GaAs Model (b) Detail Temperature of GaAs Model (c) Temperature Error in the Substrate of GaAs Model

6.2.3 Package Model

To test the use of the package sub-model two mixed-models have been built. Two models, one consists of a substrate with a single package on it and the second one with four packages, have been built. In each model, temperatures have been calculated for the package model at the point where maximum temperature is reached and also at sixteen different points of interest for both detailed and sub-model. Table 6.6 shows the temperatures for a single package model for both detailed and sub-model and corresponding errors for right-side BC and $\alpha = 10^{-8} \text{W}/\mu\text{m}^2\text{K}$.

Table 6.6: Output Temperatures for Detailed and Sub-models and Corresponding Errors for Single Package Model with Right-side BC and $\alpha = 10^{-8} \text{W}/\mu\text{m}^2\text{K}$

Output	T _{full} (K)	T _{sub} (K)	Error
<i>T-max</i>	346.941185	346.5886	0.007511
<i>P1</i>	323.361377	322.2910	0.045818
<i>P2</i>	327.192993	325.7831	0.051848
<i>P3</i>	327.193163	325.7805	0.051949
<i>P4</i>	323.361791	322.2934	0.045732
<i>P5</i>	327.271009	325.7765	0.054802
<i>P6</i>	336.200138	335.5783	0.017178
<i>P7</i>	336.200296	335.5648	0.017555
<i>P8</i>	327.271402	325.7682	0.055120
<i>P9</i>	327.271182	325.7785	0.054735
<i>P10</i>	336.200304	335.5803	0.017127
<i>P11</i>	336.200468	335.5824	0.017073
<i>P12</i>	327.271574	325.7693	0.055086
<i>P13</i>	323.361809	322.2992	0.045485
<i>P14</i>	327.193410	325.7819	0.051906
<i>P15</i>	327.193574	325.7816	0.051923
<i>P16</i>	323.362224	322.2977	0.045566

It has been observed from table 6.6 that the errors are small (within 6%) when a detailed model is represented with a single package sub-model with three-port configuration.

Figure 6.8 (a) and Figure 6.8 (b) show the substrate temperature of a detailed package model and mixed-model. It has been observed from the figures that the maximum temperature is reached at the centre (appearing as red) of the sub-model attachment.

Figure 6.8 (a): Temperatures for Substrate of Package Model Using Detailed Model

Figure 6.8 (b): Temperatures for Substrate of Package Model Using Sub-model

Table 6.7 and Table 6.8 show the temperatures for mixed-model with four attached packages for both detailed and sub-models (results for two sub-models are shown here) and corresponding errors for right-side BC and back-side BC respectively. The results for other sub-models are shown in Table C.3.1 (for right-side BC) and Table C.3.2 (for back-side BC) of Appendix C.

Table 6.7: Output Temperatures for Detailed and Two Sub-models and Corresponding Errors of Four-Package Model with Right-side BC and $\alpha = 10^{-8}$ W/ $\mu\text{m}^2\text{K}$

Output	Model-1			Model -2		
	T full	T sub	Error	T full	T sub	Error
	(K)	(K)		(K)	(K)	
<i>T-max</i>	355.732599	350.8385	0.087814	355.726242	350.7732	0.088882
<i>P1</i>	337.979876	334.6466	0.087764	338.033587	334.6149	0.089886
<i>P2</i>	340.789132	337.1676	0.088787	340.805374	337.1306	0.090056
<i>P3</i>	340.810582	337.1702	0.089202	340.785312	337.1333	0.089542
<i>P4</i>	338.039859	334.6454	0.089234	337.977182	334.6135	0.088571
<i>P5</i>	340.782258	337.1684	0.088613	340.836708	337.1315	0.090732
<i>P6</i>	347.261616	344.2088	0.064594	347.278141	344.1655	0.065837
<i>P7</i>	347.284074	344.2132	0.064945	347.257247	344.1705	0.065318
<i>P8</i>	340.843740	337.1693	0.089963	340.779106	337.1328	0.089416
<i>P9</i>	340.732886	337.1713	0.087438	340.788341	337.1343	0.089585
<i>P10</i>	347.211582	344.2014	0.063759	347.228240	344.1582	0.065004
<i>P11</i>	347.234551	344.2034	0.064172	347.206852	344.1601	0.064540
<i>P12</i>	340.795755	337.1818	0.088587	340.729384	337.1449	0.088007
<i>P13</i>	337.840758	334.6379	0.084640	337.897309	334.6060	0.086848
<i>P14</i>	340.651459	337.1766	0.085479	340.668052	337.1395	0.086765
<i>P15</i>	340.674305	337.1724	0.086096	340.646639	337.1354	0.086384
<i>P16</i>	337.904674	334.6419	0.086078	337.837056	334.6099	0.085291

Table 6.8: Output Temperatures for Detailed and Two Sub-models and Corresponding Errors of Four-Package Model with Back-side BC and $\alpha = 10^{-8}$ W/ $\mu\text{m}^2\text{K}$

Output	Model -1			Model -2		
	T _{full}	T _{sub}	Error	T _{full}	T _{sub}	Error
	(K)	(K)		(K)	(K)	
<i>T-max</i>	345.717516	344.3000	0.031006	345.717516	344.3551	0.029801
<i>P1</i>	322.352566	320.2384	0.094583	322.285907	320.1739	0.094769
<i>P2</i>	326.169762	323.6613	0.095853	326.091739	323.5894	0.095905
<i>P3</i>	326.177704	323.6583	0.096242	326.086656	323.5864	0.095844
<i>P4</i>	322.373788	320.2412	0.095316	322.271402	320.1768	0.094049
<i>P5</i>	326.244578	323.6546	0.098686	326.177442	323.5827	0.099121
<i>P6</i>	335.144228	333.3477	0.051119	335.064575	333.2648	0.051327
<i>P7</i>	335.152583	333.3325	0.051777	335.059220	333.2489	0.051636
<i>P8</i>	326.266237	323.6447	0.099806	326.162442	323.5722	0.099006
<i>P9</i>	326.251248	323.6573	0.098812	326.184300	323.5855	0.099250
<i>P10</i>	335.151051	333.3484	0.051283	335.071447	333.2654	0.051496
<i>P11</i>	335.159370	333.3513	0.051425	335.065900	333.2685	0.051258
<i>P12</i>	326.272799	323.6494	0.099852	326.168767	323.5774	0.099025
<i>P13</i>	322.371430	320.2457	0.095020	322.305300	320.1813	0.095224
<i>P14</i>	326.188554	323.6625	0.096456	326.110667	323.5910	0.096500
<i>P15</i>	326.196382	323.6604	0.096807	326.105048	323.5885	0.096401
<i>P16</i>	322.392312	320.2459	0.095855	322.289256	320.1816	0.094559

It has been observed from the above tables that the errors are within satisfactory limit (within 10 % for both right-side and back-side BC) when the detailed model is represented with four sub-models with right-side and back-side BC.

Figure 6.9 shows the temperature of the sub-models when the detailed model of the package model is represented with four sub-models. This figure also shows that the maximum temperature (appearing as red) is reached at the centre of each sub-model.

Figure 6.10 shows the temperature of the sub-model for right-side BC.

6.9: Temperature of Sub-models for Package Model

(a)

(b)

(c)

**Figure 6.10: (a) Temperature Contours for Sub-models of Package Model
 (b) Temperature Contours for Sub-models of Package Model for Right-side BC
 (c) Temperatures of Package Model for Right-side BC**

Table 6.9 shows the temperature rise and maximum error while using linear and non-linear substrate. The errors presented here indicate that the primary source of error is not due to the use of a non-linear substrate but just due to the use of sub-models and the port-configuration selected. The large errors of 59 and 60% for the case of backside BC are due to the thin substrate placing a strong constraint on the temperature profile of the substrate near the attached sub-models. For this case accurate solutions can only be obtained by using a sub-model with more ports.

Table 6.9: Temperature Rise and Maximum Error for Linear and Non-linear Substrate of Package Model

Package	Substrate	Absolute Error (K)	Maximum Error (%)
Single-package Right-side BC	linear	2.40	15.8
	non-linear	2.40	16.0
Four-packages Right-side BC	linear	6.01	18.1
	non-linear	5.56	16.9
Four-packages Back-side BC	linear	5.30	59.0
	non-linear	5.40	60.0

6.11: Temperature Errors of Sub-models for Package Model

Figure 6.11 shows the errors in temperature of the sub-model when the detailed model is represented with four-package models. The red color at the centre of each sub-model denotes that the maximum error for each sub-model is reached at the centre (inner ring) of the region where the sub-model is attached.

6.3 Speed-up Using Mixed-model

In order to clearly show the advantage of using sub-models the simulation time of the three examples presented above have been collected. Table 6.10 shows the simulation time and the number of blocks for full and mixed-model for each of the three package models.

Table 6.10: Simulation Time and Number of Blocks for Full-model and Mixed-model

Model	Time (sec.)		Number of Blocks	
	Full	Mixed	Full	Mixed
<i>GaN</i>	420.0	5.110	168221	18213
<i>GaAs</i>	1380.9	20.850	270156	69876
<i>Package</i>	100.5	0.669	80064	11480

It has been observed from Table 6.10 that the model simulation is significantly faster (60 – 150 times approximately) when a model is represented with a mixed-model. The speed-up is determined by the number of blocks in the base-model and fully detailed model. This shows the need to correctly define the sub-models to be used and the geometry of the base-model. The trade-off that is present in the sub-models is inability to predict a

detailed temperature distribution in the component and the introduction of error by the use of ports. There also is, of course, the need to create the non-linear sub-model.

6.4 Summary

This chapter shows that the detailed model of all the three package models can be effectively represented with a number of sub-models. Mixed-model simulation is significantly faster than that of the original detailed model. In the next chapter the conclusions of this thesis as well as the future research directions are stated.

Chapter 7

Conclusions

This chapter summarizes the work presented in this thesis. Also, it provides a direction of future research work.

7.1 Summary

It is very difficult to mathematically represent the non-linear thermal behavior of a detailed package model. In this thesis, non-linear thermal modeling based on neural network approach has been utilized to represent a detailed thermal model. The complex part of a detailed model has been replaced with a simple relationship by representing the detailed model with a mixed-model consisting of a base-model and a number of sub-models. The specific tasks performed to represent a detailed non-linear model of the three package models, as mentioned in the thesis, are as follows:

- First, linear thermal simulations have been performed on both detailed component-model and sub-models with different port configurations for three package models by using *Atar* for a variety of BC applied to the base-model. The accuracy of the sub-

models has been determined by calculating the errors at different temperatures of interest with respect to that of the detailed model. By using sub-modeling approach, specifically, by comparing the accuracy of sub-models with various BC, the appropriate port configuration, i.e., the number of inputs for neural network modeling has been successfully determined.

- Secondly, after deciding the number of inputs, neural network models have been developed for each of the three package models by using a neural network-based modeling tool namely, *Neuromodeler*. This has been done by training the model with a set of training data that was generated by performing non-linear simulation of *Atar*. Each of the three package models has been trained using both back propagation and conjugate gradient training method for three-layer as well as four-layer perceptrons network. After comparing the training error, it has been observed that all the models were trained well for three-layer perceptions network for both back propagation and conjugate gradient training method. Four-layer perceptrons network was found to be difficult to train.
- Next, the accuracy of the trained models has been tested with a set of testing data generated by *Atar*. It has been observed that the average and maximum testing error for all the models were within satisfactory limit. This indicates that the models developed using *Neuromodeler* is able to represent all the three package models with sufficient accuracy.

- Finally, a detailed model of each of the three package models has been represented by a number of sub-models. Temperatures at different points of interest of the sub-models have been determined in an iterative way by utilizing the MATLAB/C code generated by *Neuromodeler*. This code essentially represents the neural models of the package models under consideration. These temperatures of various points of the sub-models have been compared with that of the detailed model. It has been observed that the calculated errors of the temperatures are within satisfactory limit. This indicates that the overall thermal behavior of a detailed model can be represented with sufficient accuracy by partitioning it into a number of sub-models.

7.2 Future Research Directions

There are a number of improvements that could be undertaken in order to achieve even better results using the methodology presented in this thesis. This research can be improved and extended in the following ways:

- There is a scope for further research to investigate other possible ways of port selection for the sub-model.
- The training error of the neural model might be reduced by adjusting various parameters; for example, momentum factor and learning rate of back propagation training algorithm. Moreover, better results may be achieved by adjusting the number of hidden neurons of the neural network.
- Rules such as $\sum I_p + P = 0$ might be used in neural network.

- Investigation of transient thermal modeling utilizing neural networks would be a very challenging problem.

Appendix A

Simulation Results

A.1 GaN Based Power Package Amplifier

Table A.1.1: The Output Temperatures of GaN Model (Case – 1 in Table 4.1)

Points	T_detail (K)	T_9port (K)	T_7port (K)	T_5port (K)	T_4port (K)	T_2port (K)	T_1port (K)
<i>I1_1</i>	309.32	309.68	309.64	309.55	309.64	309.57	309.57
<i>I1_2</i>	310.35	310.61	310.61	310.53	310.59	310.53	310.53
<i>I1_3</i>	309.53	309.84	309.81	309.77	309.78	309.74	309.74
<i>I1_4</i>	309.86	310.14	310.05	309.96	310.06	309.98	309.97
<i>I1_5</i>	311.12	311.27	311.24	311.17	311.23	311.17	311.17
<i>I1_6</i>	310.10	310.32	310.23	310.19	310.20	310.16	310.16
<i>I2_1</i>	310.30	310.30	310.17	310.07	310.19	310.09	310.08
<i>I2_2</i>	311.63	311.49	311.43	311.36	311.42	311.35	311.35
<i>I2_3</i>	310.54	310.47	310.34	310.30	310.31	310.27	310.27
<i>I2_4</i>	310.51	310.43	310.29	310.18	310.31	310.20	310.20
<i>I2_5</i>	311.45	311.29	311.21	311.14	311.21	311.14	311.14
<i>I2_6</i>	310.55	310.46	310.33	310.30	310.31	310.28	310.27
<i>I3_1</i>	310.03	310.28	310.16	310.07	310.19	310.09	310.09
<i>I3_2</i>	311.24	311.35	311.28	311.22	311.29	311.22	311.22
<i>I3_3</i>	310.23	310.43	310.33	310.32	310.31	310.29	310.29
<i>I3_4</i>	309.80	310.02	309.93	309.84	309.96	309.87	309.87
<i>I3_5</i>	310.51	310.63	310.57	310.51	310.58	310.51	310.51
<i>I3_6</i>	309.78	309.99	309.90	309.91	309.90	309.89	309.88
<i>PM1</i>	306.50	306.67	306.10	305.72	306.12	305.73	305.65
<i>PM2</i>	306.60	306.50	305.83	305.55	305.79	305.54	305.43
<i>PM3</i>	302.82	302.71	302.69	305.28	302.69	305.28	305.13
<i>PB1</i>	305.31	305.79	305.85	305.76	305.86	305.80	305.80
<i>PB2</i>	305.42	305.77	305.81	305.75	305.77	305.70	305.71
<i>PB3</i>	305.44	305.83	305.79	305.73	305.84	305.77	305.78
<i>PB4</i>	305.56	305.83	305.79	305.75	305.77	305.71	305.72

Table A.1.2: Calculated Errors for Output Temperatures of GaN Model (Case – 1 in Table 4.1)

Points	E_9ports	E_7ports	E_5ports	E_4ports	E_2ports	E_1port
<i>II 1</i>	0.038627	0.034335	0.024678	0.034335	0.026824	0.026824
<i>II 2</i>	0.025121	0.025121	0.017391	0.023188	0.017391	0.017391
<i>II 3</i>	0.032529	0.029381	0.025184	0.026233	0.022036	0.022036
<i>II 4</i>	0.028398	0.019270	0.010142	0.020284	0.012170	0.011156
<i>II 5</i>	0.013489	0.010791	0.004496	0.009892	0.004496	0.004496
<i>II 6</i>	0.021782	0.012871	0.008911	0.009901	0.005941	0.005941
<i>I2 1</i>	0.000000	0.012621	0.022330	0.010680	0.020388	0.021359
<i>I2 2</i>	0.012038	0.017197	0.023216	0.018057	0.024076	0.024076
<i>I2 3</i>	0.006641	0.018975	0.022770	0.021822	0.025617	0.025617
<i>I2 4</i>	0.007612	0.020932	0.031399	0.019029	0.029496	0.029496
<i>I2 5</i>	0.013974	0.020961	0.027074	0.020961	0.027074	0.027074
<i>I2 6</i>	0.008531	0.020853	0.023697	0.022749	0.025592	0.026540
<i>I3 1</i>	0.024925	0.012961	0.003988	0.015952	0.005982	0.005982
<i>I3 2</i>	0.009786	0.003559	0.001779	0.004448	0.001779	0.001779
<i>I3 3</i>	0.019550	0.009775	0.008798	0.007820	0.005865	0.005865
<i>I3 4</i>	0.022449	0.013265	0.004082	0.016327	0.007143	0.007143
<i>I3 5</i>	0.011418	0.005709	0.000000	0.006660	0.000000	0.000000
<i>I3 6</i>	0.021472	0.012270	0.013292	0.012270	0.011247	0.010225
<i>PM1</i>	0.026154	0.061538	0.120000	0.058462	0.118462	0.130769
<i>PM2</i>	0.015152	0.116667	0.159091	0.122727	0.160606	0.177273
<i>PM3</i>	0.039007	0.046099	0.872340	0.046099	0.872340	0.819149
<i>PB1</i>	0.090395	0.101695	0.084746	0.103578	0.092279	0.092279
<i>PB2</i>	0.064576	0.071956	0.060886	0.064576	0.051661	0.053506
<i>PB3</i>	0.071691	0.064338	0.053309	0.073529	0.060662	0.062500
<i>PB4</i>	0.048561	0.041367	0.034173	0.037770	0.026978	0.028777

Table A.1.3: The Output Temperatures of GaN Model (Case – 3 in Table 4.1)

Points	T_detail (K)	T_9port (K)	T_7port (K)	T_5port (K)	T_4port (K)	T_2port (K)	T_1port (K)
<i>I1_1</i>	310.19	310.57	310.52	310.44	310.55	310.48	310.48
<i>I1_2</i>	311.22	311.49	311.49	311.42	311.50	311.44	311.45
<i>I1_3</i>	310.40	310.73	310.69	310.65	310.69	310.65	310.65
<i>I1_4</i>	310.76	311.04	310.94	310.86	310.97	310.89	310.89
<i>I1_5</i>	312.00	312.17	312.13	312.07	312.14	312.08	312.08
<i>I1_6</i>	310.99	311.21	311.12	311.09	311.11	311.08	311.08
<i>I2_1</i>	311.22	311.22	311.07	310.98	311.09	311.01	311.00
<i>I2_2</i>	312.53	312.39	312.33	312.27	312.33	312.27	312.27
<i>I2_3</i>	311.44	311.38	311.24	311.21	311.22	311.19	311.19
<i>I2_4</i>	311.44	311.35	311.20	311.11	311.22	311.12	311.11
<i>I2_5</i>	312.37	312.21	312.13	312.07	312.12	312.06	312.06
<i>I2_6</i>	311.48	311.38	311.24	311.22	311.22	311.20	311.19
<i>I3_1</i>	310.98	311.22	311.09	311.01	311.10	311.01	311.00
<i>I3_2</i>	312.18	312.29	312.21	312.16	312.20	312.14	312.14
<i>I3_3</i>	311.18	311.36	311.25	311.25	311.23	311.21	311.21
<i>I3_4</i>	310.76	310.97	310.86	310.79	310.87	310.79	310.78
<i>I3_5</i>	311.47	311.58	311.50	311.45	311.49	311.43	311.43
<i>I3_6</i>	310.74	310.93	310.84	310.85	310.81	310.81	310.80
<i>PM1</i>	307.46	307.61	307.01	306.65	307.04	306.68	306.56
<i>PM2</i>	307.51	307.42	306.72	306.49	306.70	306.49	306.35
<i>PM3</i>	304.00	303.89	303.87	306.23	303.86	306.24	306.04
<i>PB1</i>	306.17	306.67	306.73	306.66	306.77	306.71	306.72
<i>PB2</i>	306.27	306.64	306.68	306.63	306.67	306.62	306.63
<i>PB3</i>	306.42	306.79	306.74	306.69	306.75	306.69	306.70
<i>PB4</i>	306.52	306.78	306.73	306.70	306.68	306.63	306.63

Table A.1.4: Calculated Errors for Output Temperatures of GaN Model (Case – 3 in Table 4.1)

Points	E_9ports	E_7ports	E_5ports	E_4ports	E_2ports	E_1port
<i>I1_1</i>	0.037291	0.032385	0.024534	0.035329	0.028459	0.028459
<i>I1_2</i>	0.024064	0.024064	0.017825	0.024955	0.019608	0.020499
<i>I1_3</i>	0.031731	0.027885	0.024038	0.027885	0.024038	0.024038
<i>I1_4</i>	0.026022	0.016729	0.009294	0.019517	0.012082	0.012082
<i>I1_5</i>	0.014167	0.010833	0.005833	0.011667	0.006667	0.006667
<i>I1_6</i>	0.020018	0.011829	0.009099	0.010919	0.008189	0.008189
<i>I2_1</i>	0.000000	0.013369	0.021390	0.011586	0.018717	0.019608
<i>I2_2</i>	0.011173	0.015962	0.020750	0.015962	0.020750	0.020750
<i>I2_3</i>	0.005245	0.017483	0.020105	0.019231	0.021853	0.021853
<i>I2_4</i>	0.007867	0.020979	0.028846	0.019231	0.027972	0.028846
<i>I2_5</i>	0.012935	0.019402	0.024252	0.020210	0.025061	0.025061

<i>I2_6</i>	0.008711	0.020906	0.022648	0.022648	0.024390	0.025261
<i>I3_1</i>	0.021858	0.010018	0.002732	0.010929	0.002732	0.001821
<i>I3_2</i>	0.009031	0.002463	0.001642	0.001642	0.003284	0.003284
<i>I3_3</i>	0.016100	0.006261	0.006261	0.004472	0.002683	0.002683
<i>I3_4</i>	0.019517	0.009294	0.002788	0.010223	0.002788	0.001859
<i>I3_5</i>	0.009590	0.002616	0.001744	0.001744	0.003487	0.003487
<i>I3_6</i>	0.017691	0.009311	0.010242	0.006518	0.006518	0.005587
<i>PM1</i>	0.020107	0.060322	0.108579	0.056300	0.104558	0.120643
<i>PM2</i>	0.011984	0.105193	0.135819	0.107856	0.135819	0.154461
<i>PM3</i>	0.027500	0.032500	0.557500	0.035000	0.560000	0.510000
<i>PB1</i>	0.081037	0.090762	0.079417	0.097245	0.087520	0.089141
<i>PB2</i>	0.059011	0.065391	0.057416	0.063796	0.055821	0.057416
<i>PB3</i>	0.057632	0.049844	0.042056	0.051402	0.042056	0.043614
<i>PB4</i>	0.039877	0.032209	0.027607	0.024540	0.016871	0.016871

Table A.1.5: The Output Temperatures of GaN Model (Case – 4 in Table 4.1)

Points	T_detail (K)	T_9port (K)	T_7port (K)	T_5port (K)	T_4port (K)	T_2port (K)	T_1port (K)
<i>I1_1</i>	310.47	310.81	310.77	310.65	310.73	310.64	310.64
<i>I1_2</i>	311.49	311.73	311.73	311.64	311.68	311.60	311.60
<i>I1_3</i>	310.66	310.96	310.93	310.87	310.87	310.81	310.81
<i>I1_4</i>	311.00	311.26	311.18	311.06	311.15	311.05	311.05
<i>I1_5</i>	312.25	312.39	312.36	312.27	312.33	312.24	312.24
<i>I1_6</i>	311.22	311.42	311.34	311.28	311.29	311.24	311.23
<i>I2_1</i>	311.41	311.41	311.28	311.15	311.28	311.16	311.16
<i>I2_2</i>	312.73	312.59	312.53	312.44	312.52	312.43	312.43
<i>I2_3</i>	311.63	311.56	311.44	311.38	311.40	311.35	311.34
<i>I2_4</i>	311.6	311.52	311.38	311.25	311.40	311.27	311.27
<i>I2_5</i>	312.52	312.37	312.30	312.21	312.31	312.22	312.22
<i>I2_6</i>	311.62	311.53	311.41	311.37	311.40	311.35	311.35
<i>I3_1</i>	311.10	311.36	311.24	311.12	311.28	311.16	311.16
<i>I3_2</i>	312.29	312.42	312.35	312.27	312.38	312.29	312.29
<i>I3_3</i>	311.28	311.49	311.39	311.37	311.40	311.37	311.36
<i>I3_4</i>	310.85	311.09	311.00	310.89	311.05	310.94	310.94
<i>I3_5</i>	311.55	311.69	311.63	311.55	311.67	311.59	311.59
<i>I3_6</i>	310.80	311.03	310.96	310.95	310.98	310.96	310.96
<i>PM1</i>	307.64	307.79	307.23	306.79	307.22	306.79	306.72
<i>PM2</i>	307.69	307.60	306.95	306.61	306.89	306.59	306.50
<i>PM3</i>	303.52	303.42	303.40	306.33	303.40	306.31	306.20
<i>PB1</i>	306.48	306.93	306.99	306.88	306.95	306.87	306.87
<i>PB2</i>	306.57	306.89	306.94	306.86	306.86	306.78	306.78
<i>PB3</i>	306.47	306.89	306.85	306.77	306.93	306.85	306.85
<i>PB4</i>	306.57	306.87	306.83	306.78	306.86	306.79	306.79

Table A.1.6: Calculated Errors for Output Temperatures of GaN Model (Case – 4 in Table 4.1)

Points	E_9ports	E_7ports	E_5ports	E_4ports	E_2ports	E_1port
<i>II 1</i>	0.032474	0.028653	0.017192	0.024833	0.016237	0.016237
<i>II 2</i>	0.020888	0.020888	0.013055	0.016536	0.009574	0.009574
<i>II 3</i>	0.028143	0.025328	0.019700	0.019700	0.014071	0.014071
<i>II 4</i>	0.023636	0.016364	0.005455	0.013636	0.004545	0.004545
<i>II 5</i>	0.011429	0.008980	0.001633	0.006531	0.000816	0.000816
<i>II 6</i>	0.017825	0.010695	0.005348	0.006239	0.001783	0.000891
<i>I2 1</i>	0.000000	0.011394	0.022787	0.011394	0.021911	0.021911
<i>I2 2</i>	0.010998	0.015711	0.022781	0.016496	0.023566	0.023566
<i>I2 3</i>	0.006019	0.016337	0.021496	0.019776	0.024076	0.024936
<i>I2 4</i>	0.006897	0.018966	0.030172	0.017241	0.028448	0.028448
<i>I2 5</i>	0.011981	0.017572	0.024760	0.016773	0.023962	0.023962
<i>I2 6</i>	0.007745	0.018072	0.021515	0.018933	0.023236	0.023236
<i>I3 1</i>	0.023423	0.012613	0.001802	0.016216	0.005405	0.005405
<i>I3 2</i>	0.010578	0.004882	0.001627	0.007323	0.000000	0.000000
<i>I3 3</i>	0.018617	0.009752	0.007979	0.010638	0.007979	0.007092
<i>I3 4</i>	0.022120	0.013825	0.003687	0.018433	0.008295	0.008295
<i>I3 5</i>	0.012121	0.006926	0.000000	0.010390	0.003463	0.003463
<i>I3 6</i>	0.021296	0.014815	0.013889	0.016667	0.014815	0.014815
<i>PM1</i>	0.019634	0.053665	0.111257	0.054974	0.111257	0.120419
<i>PM2</i>	0.011704	0.096229	0.140442	0.104031	0.143043	0.154746
<i>PM3</i>	0.028409	0.034091	0.798295	0.034091	0.792614	0.761364
<i>PB1</i>	0.069444	0.078704	0.061728	0.072531	0.060185	0.060185
<i>PB2</i>	0.048706	0.056317	0.044140	0.044140	0.031963	0.031963
<i>PB3</i>	0.064915	0.058733	0.046368	0.071097	0.058733	0.058733
<i>PB4</i>	0.045662	0.039574	0.031963	0.044140	0.033486	0.033486

Table A.1.7: The Output Temperatures of GaN Model (Case – 5 in Table 4.1)

Points	T_detail (K)	T_9port (K)	T_7port (K)	T_5port (K)	T_4port (K)	T_2port (K)	T_1port (K)
<i>II 1</i>	310.46	310.81	310.77	310.66	310.74	310.66	310.66
<i>II 2</i>	311.45	311.71	311.71	311.63	311.69	311.62	311.62
<i>II 3</i>	310.59	310.91	310.88	310.83	310.87	310.83	310.83
<i>II 4</i>	311.01	311.27	311.18	311.07	311.16	311.07	311.07
<i>II 5</i>	312.22	312.37	312.34	312.26	312.33	312.26	312.26
<i>II 6</i>	311.15	311.38	311.30	311.26	311.29	311.25	311.25
<i>I2 1</i>	311.44	311.43	311.30	311.18	311.28	311.18	311.17
<i>I2 2</i>	312.72	312.58	312.52	312.45	312.52	312.45	312.44
<i>I2 3</i>	311.59	311.53	311.40	311.37	311.41	311.36	311.36
<i>I2 4</i>	311.65	311.55	311.41	311.29	311.41	311.29	311.29

<i>I2_5</i>	312.54	312.38	312.31	312.23	312.31	312.23	312.23
<i>I2_6</i>	311.60	311.52	311.39	311.37	311.40	311.37	311.36
<i>I3_1</i>	311.16	311.40	311.28	311.18	311.29	311.18	311.18
<i>I3_2</i>	312.33	312.45	312.37	312.31	312.38	312.31	312.31
<i>I3_3</i>	311.28	311.49	311.39	311.38	311.41	311.38	311.38
<i>I3_4</i>	310.93	311.14	311.05	310.95	311.06	310.96	310.96
<i>I3_5</i>	311.60	311.73	311.66	311.60	311.67	311.61	311.61
<i>I3_6</i>	310.82	311.04	310.97	310.97	310.99	310.98	310.98
<i>PM1</i>	307.72	307.85	307.26	306.83	307.24	306.82	306.74
<i>PM2</i>	307.56	307.49	306.85	306.63	306.85	306.63	306.52
<i>PM3</i>	303.85	303.75	303.72	306.37	303.73	306.36	306.22
<i>PB1</i>	306.48	306.93	306.99	306.90	306.96	306.89	306.89
<i>PB2</i>	306.46	306.82	306.86	306.80	306.86	306.79	306.80
<i>PB3</i>	306.59	306.97	306.92	306.85	306.94	306.87	306.87
<i>PB4</i>	306.57	306.87	306.83	306.79	306.87	306.80	306.81

Table A.1.8: Calculated Errors for Output Temperatures of GaN Model (Case – 5 in Table 4.1)

Points	E_9ports	E_7ports	E_5ports	E_4ports	E_2ports	E_1port
<i>II_1</i>	0.033461	0.029637	0.019120	0.026769	0.019120	0.019120
<i>II_2</i>	0.022707	0.022707	0.015721	0.020961	0.014847	0.014847
<i>II_3</i>	0.030217	0.027384	0.022663	0.026440	0.022663	0.022663
<i>II_4</i>	0.023615	0.015441	0.005450	0.013624	0.005450	0.005450
<i>II_5</i>	0.012275	0.009820	0.003273	0.009002	0.003273	0.003273
<i>II_6</i>	0.020628	0.013453	0.009865	0.012556	0.008969	0.008969
<i>I2_1</i>	0.000874	0.012238	0.022727	0.013986	0.022727	0.023601
<i>I2_2</i>	0.011006	0.015723	0.021226	0.015723	0.021226	0.022013
<i>I2_3</i>	0.005177	0.016393	0.018982	0.015531	0.019845	0.019845
<i>I2_4</i>	0.008584	0.020601	0.030901	0.020601	0.030901	0.030901
<i>I2_5</i>	0.012759	0.018341	0.024721	0.018341	0.024721	0.024721
<i>I2_6</i>	0.006897	0.018103	0.019828	0.017241	0.019828	0.020690
<i>I3_1</i>	0.021505	0.010753	0.001792	0.011649	0.001792	0.001792
<i>I3_2</i>	0.009732	0.003244	0.001622	0.004055	0.001622	0.001622
<i>I3_3</i>	0.018617	0.009752	0.008865	0.011525	0.008865	0.008865
<i>I3_4</i>	0.019213	0.010979	0.001830	0.011894	0.002745	0.002745
<i>I3_5</i>	0.011207	0.005172	0.000000	0.006034	0.000862	0.000862
<i>I3_6</i>	0.020333	0.013863	0.013863	0.015712	0.014787	0.014787
<i>PM1</i>	0.016839	0.059585	0.115285	0.062176	0.116580	0.126943
<i>PM2</i>	0.009259	0.093915	0.123016	0.093915	0.123016	0.137566
<i>PM3</i>	0.025974	0.033766	0.654545	0.031169	0.651948	0.615584
<i>PB1</i>	0.069444	0.078704	0.064815	0.074074	0.063272	0.063272
<i>PB2</i>	0.055728	0.061920	0.052632	0.061920	0.051084	0.052632
<i>PB3</i>	0.057663	0.050076	0.039454	0.053111	0.042489	0.042489
<i>PB4</i>	0.045662	0.039574	0.033486	0.045662	0.035008	0.036530

Table A.1.9: The Output Temperatures of GaN Model (Case – 6 in Table 4.1)

Points	T_detail (K)	T_9port (K)	T_7port (K)	T_5port (K)	T_4port (K)	T_2port (K)	T_1port (K)
<i>II_1</i>	310.16	310.53	310.49	310.41	310.51	310.44	310.44
<i>II_2</i>	311.23	311.48	311.49	311.42	311.46	311.40	311.41
<i>II_3</i>	310.46	310.75	310.72	310.67	310.65	310.61	310.61
<i>II_4</i>	310.70	310.99	310.91	310.82	310.93	310.85	310.85
<i>II_5</i>	312.00	312.15	312.12	312.05	312.11	312.04	312.05
<i>II_6</i>	311.03	311.22	311.14	311.10	311.08	311.04	311.04
<i>I2_1</i>	311.14	311.15	311.02	310.93	311.06	310.97	310.96
<i>I2_2</i>	312.50	312.36	312.30	312.24	312.30	312.23	312.23
<i>I2_3</i>	311.46	311.38	311.24	311.20	311.19	311.15	311.15
<i>I2_4</i>	311.34	311.27	311.14	311.04	311.18	311.08	311.07
<i>I2_5</i>	312.32	312.16	312.08	312.02	312.09	312.02	312.02
<i>I2_6</i>	311.47	311.36	311.23	311.20	311.19	311.16	311.15
<i>I3_1</i>	310.86	311.12	311.01	310.93	311.06	310.97	310.96
<i>I3_2</i>	312.11	312.23	312.15	312.10	312.16	312.10	312.10
<i>I3_3</i>	311.15	311.33	311.23	311.22	311.19	311.17	311.17
<i>I3_4</i>	310.63	310.87	310.77	310.70	310.83	310.75	310.74
<i>I3_5</i>	311.38	311.51	311.44	311.39	311.45	311.39	311.39
<i>I3_6</i>	310.69	310.89	310.80	310.81	310.77	310.77	310.76
<i>PM1</i>	307.26	307.47	306.92	306.60	306.97	306.62	306.52
<i>PM2</i>	307.59	307.47	306.78	306.45	306.69	306.43	306.31
<i>PM3</i>	303.81	303.70	303.68	306.17	303.67	306.17	306.00
<i>PB1</i>	306.13	306.63	306.69	306.62	306.73	306.67	306.68
<i>PB2</i>	306.37	306.69	306.74	306.67	306.64	306.58	306.59
<i>PB3</i>	306.24	306.67	306.62	306.57	306.71	306.65	306.66
<i>PB4</i>	306.49	306.74	306.70	306.66	306.64	306.59	306.59

Table A.1.10: Calculated Errors for Output Temperatures of GaN Model (Case – 6 in Table 4.1)

Points	E_9ports	E_7ports	E_5ports	E_4ports	E_2ports	E_1port
<i>II_1</i>	0.036417	0.03248	0.024606	0.034449	0.027559	0.027559
<i>II_2</i>	0.022262	0.023152	0.016919	0.020481	0.015138	0.016028
<i>II_3</i>	0.027725	0.024857	0.020076	0.018164	0.014340	0.014340
<i>II_4</i>	0.027103	0.019626	0.011215	0.021495	0.014019	0.014019
<i>II_5</i>	0.012500	0.010000	0.004167	0.009167	0.003333	0.004167
<i>II_6</i>	0.017226	0.009973	0.006346	0.004533	0.000907	0.000907
<i>I2_1</i>	0.000898	0.010772	0.018851	0.007181	0.015260	0.016158
<i>I2_2</i>	0.011200	0.016000	0.020800	0.016000	0.021600	0.021600
<i>I2_3</i>	0.006981	0.019197	0.022688	0.023560	0.027051	0.027051
<i>I2_4</i>	0.006173	0.017637	0.026455	0.014109	0.022928	0.023810

<i>I2_5</i>	0.012987	0.019481	0.024351	0.018669	0.024351	0.024351
<i>I2_6</i>	0.009590	0.020924	0.023540	0.024412	0.027027	0.027899
<i>I3_1</i>	0.023941	0.013812	0.006446	0.018416	0.010129	0.009208
<i>I3_2</i>	0.009909	0.003303	0.000826	0.004129	0.000826	0.000826
<i>I3_3</i>	0.016143	0.007175	0.006278	0.003587	0.001794	0.001794
<i>I3_4</i>	0.022578	0.013170	0.006585	0.018815	0.011289	0.010348
<i>I3_5</i>	0.011424	0.005272	0.000879	0.006151	0.000879	0.000879
<i>I3_6</i>	0.018709	0.010290	0.011225	0.007484	0.007484	0.006548
<i>PM1</i>	0.028926	0.046832	0.090909	0.039945	0.088154	0.101928
<i>PM2</i>	0.015810	0.106719	0.150198	0.118577	0.152833	0.168643
<i>PM3</i>	0.028871	0.034121	0.619423	0.036745	0.619423	0.574803
<i>PB1</i>	0.081566	0.091354	0.079935	0.097879	0.088091	0.089723
<i>PB2</i>	0.050235	0.058085	0.047096	0.042386	0.032967	0.034537
<i>PB3</i>	0.068910	0.060897	0.052885	0.075321	0.065705	0.067308
<i>PB4</i>	0.038521	0.032357	0.026194	0.023112	0.015408	0.015408

A.2 GaAs Based Power Amplifier

Table A.2.1: The Output Temperatures of GaAs Model (Case – 1 in Table 4.5)

Points	T_detailed (K)	T_9ports (K)	T_5ports (K)	T_2ports (K)	T_1port (K)
<i>I1_1</i>	631.04	627.96	627.90	627.83	626.39
<i>I1_2</i>	970.91	967.70	967.61	967.42	965.86
<i>I1_3</i>	909.77	906.53	906.40	906.21	904.98
<i>I2_1</i>	642.91	639.87	639.82	639.78	638.65
<i>I2_2</i>	984.03	980.90	980.82	980.65	979.54
<i>I2_3</i>	922.60	919.40	919.28	919.09	918.22
<i>I3_1</i>	646.81	643.67	643.58	643.46	642.30
<i>I3_2</i>	989.03	985.79	985.68	985.39	984.22
<i>I3_3</i>	925.96	922.65	922.49	922.20	921.26
<i>I4_1</i>	626.95	623.54	623.36	622.89	621.23
<i>I4_2</i>	965.31	961.77	961.56	960.92	959.10
<i>I4_3</i>	906.66	903.12	902.87	902.33	900.93
<i>PM1</i>	338.29	333.81	333.72	332.91	316.54
<i>PM2</i>	345.59	340.37	340.18	333.51	317.18
<i>PM3</i>	349.01	341.77	341.68	334.22	317.70
<i>PM4</i>	323.66	320.38	320.38	331.48	315.55
<i>PB1</i>	316.89	316.37	316.46	316.49	316.92
<i>PB2</i>	317.66	316.80	316.69	316.70	317.13
<i>PB3</i>	317.01	316.42	316.43	316.45	316.90
<i>PB4</i>	315.71	315.74	316.06	316.11	316.52
<i>PB5</i>	323.82	321.20	321.51	321.53	321.85

Table A.2.2: Calculated Errors for Output Temperatures of GaAs Model (Case – 1 in Table 4.5)

Points	E_9ports	E_5ports	E_2ports	E_1port
<i>I1_1</i>	0.009304	0.009485	0.009697	0.014047
<i>I1_2</i>	0.005313	0.005527	0.005838	0.007855
<i>I1_3</i>	0.008865	0.009011	0.009128	0.012423
<i>I2_1</i>	0.004576	0.004693	0.004941	0.006564
<i>I2_2</i>	0.005140	0.005332	0.005638	0.007035
<i>I2_3</i>	0.009054	0.009313	0.009659	0.013004
<i>I3_1</i>	0.004702	0.004862	0.005283	0.006981
<i>I3_2</i>	0.005288	0.005543	0.006007	0.007508
<i>I3_3</i>	0.010430	0.010980	0.012418	0.017495

<i>I4_1</i>	0.005321	0.005636	0.006598	0.009334
<i>I4_2</i>	0.005835	0.006247	0.007137	0.009445
<i>I4_3</i>	0.117002	0.119352	0.140507	0.568033
<i>PM1</i>	0.114499	0.118666	0.264970	0.623163
<i>PM2</i>	0.147725	0.149561	0.301775	0.638849
<i>PM3</i>	0.138631	0.138631	0.330516	0.342773
<i>PM4</i>	0.030787	0.025459	0.023683	0.001776
<i>PB1</i>	0.048698	0.054926	0.054360	0.030011
<i>PB2</i>	0.034685	0.034098	0.032922	0.006467
<i>PB3</i>	0.001910	0.022279	0.025461	0.051560
<i>PB4</i>	0.109992	0.096977	0.096138	0.082704
<i>PB5</i>	0.009304	0.009485	0.009697	0.014047

Table A.2.3: The Output Temperatures of GaAs Model (Case – 2 in Table 4.5)

Points	T_detailed (K)	T_9ports (K)	T_5ports (K)	T_2ports (K)	T_1port (K)
<i>I1_1</i>	631.44	628.35	628.27	628.20	626.69
<i>I1_2</i>	971.31	968.10	967.99	967.79	966.16
<i>I1_3</i>	910.17	906.92	906.77	906.57	905.29
<i>I2_1</i>	643.29	640.25	640.18	640.15	638.96
<i>I2_2</i>	984.42	981.28	981.19	981.01	979.85
<i>I2_3</i>	922.98	919.78	919.64	919.44	918.52
<i>I3_1</i>	647.20	644.05	643.95	643.82	642.60
<i>I3_2</i>	989.42	986.18	986.05	985.75	984.53
<i>I3_3</i>	926.34	923.03	922.85	922.56	921.57
<i>I4_1</i>	627.36	623.94	623.74	623.26	621.53
<i>I4_2</i>	965.72	962.18	961.95	961.30	959.40
<i>I4_3</i>	907.06	903.52	903.25	902.70	901.24
<i>PM1</i>	339.03	334.57	334.46	333.64	316.85
<i>PM2</i>	346.36	341.16	340.94	334.24	317.49
<i>PM3</i>	349.88	342.68	342.55	334.96	318.00
<i>PM4</i>	324.28	321.02	321.00	332.20	315.86
<i>PB1</i>	317.21	316.70	316.79	316.81	317.23
<i>PB2</i>	317.99	317.13	317.01	317.02	317.44
<i>PB3</i>	317.33	316.75	316.75	316.77	317.21
<i>PB4</i>	316.02	316.06	316.38	316.44	316.83
<i>PB5</i>	324.12	321.51	321.84	321.85	322.16

Table A.2.4: Calculated Errors for Output Temperatures of GaAs Model (Case – 2 in Table 4.5)

Points	E_9ports	E_5ports	E_2ports	E_1port
<i>II_1</i>	0.009323	0.009564	0.009776	0.014331
<i>II_2</i>	0.004782	0.004946	0.005243	0.007672
<i>II_3</i>	0.005326	0.005572	0.005900	0.007998
<i>I2_1</i>	0.008855	0.009059	0.009147	0.012613
<i>I2_2</i>	0.004588	0.004719	0.004982	0.006677
<i>I2_3</i>	0.005137	0.005361	0.005682	0.007159
<i>I3_1</i>	0.009073	0.009361	0.009735	0.013249
<i>I3_2</i>	0.004700	0.004888	0.005323	0.007093
<i>I3_3</i>	0.005285	0.005572	0.006035	0.007616
<i>I4_1</i>	0.010447	0.011058	0.012524	0.017809
<i>I4_2</i>	0.005318	0.005663	0.006639	0.009493
<i>I4_3</i>	0.005831	0.006276	0.007182	0.009587
<i>PM1</i>	0.114271	0.117089	0.138099	0.568281
<i>PM2</i>	0.112166	0.116911	0.261432	0.622735
<i>PM3</i>	0.144346	0.146953	0.299118	0.639134
<i>PM4</i>	0.134267	0.135091	0.326194	0.346787
<i>PB1</i>	0.029634	0.024404	0.023242	0.001162
<i>PB2</i>	0.047804	0.054475	0.053919	0.030573
<i>PB3</i>	0.033468	0.033468	0.032314	0.006924
<i>PB4</i>	0.002497	0.022472	0.026217	0.050562
<i>PB5</i>	0.108209	0.094527	0.094113	0.081260

Table A.2.5: The Output Temperatures of GaAs Model (Case – 4 in Table 4.5)

Points	T_detailed (K)	T_9ports (K)	T_5ports (K)	T_2ports (K)	T_1port (K)
<i>II_1</i>	673.69	668.11	666.71	666.18	665.19
<i>II_2</i>	1013.61	1007.89	1006.44	1005.75	1004.66
<i>II_3</i>	952.49	946.69	945.21	944.59	943.79
<i>I2_1</i>	684.16	679.32	678.39	678.19	677.46
<i>I2_2</i>	1025.31	1020.37	1019.40	1019.06	1018.35
<i>I2_3</i>	963.93	958.90	957.88	957.54	957.02
<i>I3_1</i>	686.60	682.45	681.97	681.86	681.10
<i>I3_2</i>	1028.84	1024.56	1024.04	1023.79	1023.02
<i>I3_3</i>	965.80	961.47	960.91	960.64	960.06
<i>I4_1</i>	664.72	661.03	661.07	661.20	660.03
<i>I4_2</i>	1002.97	999.12	999.13	999.20	997.90
<i>I4_3</i>	944.55	940.73	940.69	940.69	939.74
<i>PM1</i>	384.84	377.76	376.01	368.62	355.35
<i>PM2</i>	371.80	365.68	365.93	369.23	355.99

<i>PM3</i>	388.84	380.06	379.22	369.90	356.50
<i>PM4</i>	363.42	358.80	358.21	367.27	354.36
<i>PB1</i>	362.81	357.49	355.24	355.17	355.73
<i>PB2</i>	354.21	354.91	355.43	355.38	355.94
<i>PB3</i>	360.31	356.45	355.20	355.13	355.70
<i>PB4</i>	358.73	355.72	354.83	354.79	355.33
<i>PB5</i>	367.38	361.59	360.27	360.19	360.65

Table A.2.6: Calculated Errors for Output Temperatures of GaAs Model (Case – 4 in Table 4.5)

Points	E 9ports	E 5ports	E 2ports	E 1port
<i>I1 1</i>	0.014932	0.018679	0.020097	0.022746
<i>I1 2</i>	0.008016	0.010048	0.011014	0.012542
<i>I1 3</i>	0.008889	0.011157	0.012107	0.013334
<i>I2 1</i>	0.012599	0.015020	0.015540	0.017441
<i>I2 2</i>	0.006811	0.008148	0.008617	0.009596
<i>I2 3</i>	0.007576	0.009112	0.009625	0.010408
<i>I3 1</i>	0.010735	0.011976	0.012261	0.014227
<i>I3 2</i>	0.005872	0.006586	0.006929	0.007985
<i>I3 3</i>	0.006503	0.007345	0.007750	0.008621
<i>I4 1</i>	0.010117	0.010008	0.009651	0.012859
<i>I4 2</i>	0.005477	0.005463	0.005363	0.007212
<i>I4 3</i>	0.005927	0.005989	0.005989	0.007463
<i>PM1</i>	0.083451	0.104078	0.191183	0.347595
<i>PM2</i>	0.085237	0.081755	0.035794	0.220195
<i>PM3</i>	0.098829	0.108285	0.213192	0.364025
<i>PM4</i>	0.072848	0.082151	0.060706	0.142857
<i>PB1</i>	0.084700	0.120522	0.121637	0.112721
<i>PB2</i>	0.012913	0.022505	0.021583	0.031913
<i>PB3</i>	0.064003	0.084729	0.085890	0.076438
<i>PB4</i>	0.051251	0.066406	0.067087	0.057892
<i>PB5</i>	0.085931	0.105521	0.106708	0.099881

Table A.2.7: The Output Temperatures of GaAs Model (Case – 5 in Table 4.5)

Points	T_detailed (K)	T_9ports (K)	T_5ports (K)	T_2ports (K)	T_1port (K)
<i>I1_1</i>	671.97	667.49	666.78	666.20	665.21
<i>I1_2</i>	1012.79	1007.63	1006.59	1005.76	1004.68
<i>I1_3</i>	952.57	946.81	945.42	944.61	943.80
<i>I2_1</i>	683.85	679.36	678.66	678.20	677.47
<i>I2_2</i>	1025.94	1020.85	1019.79	1019.07	1018.36
<i>I2_3</i>	965.42	959.72	958.29	957.55	957.04
<i>I3_1</i>	687.79	683.19	682.45	681.87	681.12
<i>I3_2</i>	1030.99	1025.77	1024.67	1023.80	1023.04
<i>I3_3</i>	968.82	963.00	961.53	960.65	960.08
<i>I4_1</i>	667.87	663.05	662.21	661.21	660.05
<i>I4_2</i>	1007.17	1001.66	1000.50	999.21	997.92
<i>I4_3</i>	949.43	943.35	941.85	940.70	939.75
<i>PM1</i>	378.97	372.71	371.75	368.64	355.36
<i>PM2</i>	386.48	379.40	378.28	369.25	356.00
<i>PM3</i>	396.76	387.04	385.29	369.92	356.52
<i>PM4</i>	351.76	347.76	348.46	367.29	354.37
<i>PB1</i>	360.88	356.86	355.51	355.18	355.74
<i>PB2</i>	361.77	357.30	355.73	355.39	355.95
<i>PB3</i>	363.87	358.02	355.47	355.15	355.72
<i>PB4</i>	352.71	354.25	355.07	354.80	355.34
<i>PB5</i>	368.18	362.05	360.54	360.20	360.67

Table A.2.8: Calculated Errors for Output Temperatures of GaAs Model (Case – 5 in Table 4.5)

Points	E_9ports	E_5ports	E_2ports	E_1port
<i>I1_1</i>	0.012044	0.013953	0.015512	0.018174
<i>I1_2</i>	0.007239	0.008698	0.009863	0.011378
<i>I1_3</i>	0.008827	0.010957	0.012198	0.013439
<i>I2_1</i>	0.011697	0.013521	0.014719	0.016621
<i>I2_2</i>	0.007012	0.008472	0.009464	0.010442
<i>I2_3</i>	0.008566	0.010715	0.011827	0.012594
<i>I3_1</i>	0.011862	0.013770	0.015266	0.017200
<i>I3_2</i>	0.007141	0.008646	0.009836	0.010876
<i>I3_3</i>	0.008702	0.010900	0.012216	0.013068
<i>I4_1</i>	0.013102	0.015386	0.018104	0.021258
<i>I4_2</i>	0.007792	0.009432	0.011256	0.013080
<i>I4_3</i>	0.009362	0.011672	0.013443	0.014905
<i>PM1</i>	0.079271	0.091427	0.130809	0.298974
<i>PM2</i>	0.081869	0.094820	0.199237	0.352451
<i>PM3</i>	0.100455	0.118541	0.277387	0.415874

<i>PM4</i>	0.077280	0.063756	0.300039	0.050425
<i>PB1</i>	0.066032	0.088206	0.093627	0.084428
<i>PB2</i>	0.072365	0.097782	0.103286	0.094220
<i>PB3</i>	0.091592	0.131517	0.136527	0.127603
<i>PB4</i>	0.029216	0.044773	0.039651	0.049896
<i>PB5</i>	0.089909	0.112056	0.117043	0.110150

Table A.2.9: The Output Temperatures of GaAs Model (Case – 6 in Table 4.5)

Points	T_detailed	T_9ports	T_5ports	T_2ports	T_1port
	(K)	(K)	(K)	(K)	(K)
<i>I1_1</i>	672.01	667.14	666.23	666.20	665.21
<i>I1_2</i>	1010.97	1006.47	1005.81	1005.76	1004.68
<i>I1_3</i>	948.97	945.01	944.66	944.61	943.80
<i>I2_1</i>	683.96	679.13	678.19	678.20	677.47
<i>I2_2</i>	1024.22	1019.76	1019.08	1019.07	1018.36
<i>I2_3</i>	961.91	957.93	957.58	957.55	957.04
<i>I3_1</i>	687.83	682.88	681.91	681.87	681.12
<i>I3_2</i>	1029.16	1024.57	1023.86	1023.80	1023.04
<i>I3_3</i>	965.21	961.11	960.72	960.65	960.08
<i>I4_1</i>	668.02	662.79	661.77	661.21	660.05
<i>I4_2</i>	1005.53	1000.66	999.88	999.21	997.92
<i>I4_3</i>	946.00	941.71	941.23	940.70	939.75
<i>PM1</i>	377.93	372.11	371.41	368.64	355.36
<i>PM2</i>	385.45	378.80	377.95	369.25	356.00
<i>PM3</i>	372.90	363.93	363.85	369.92	356.52
<i>PM4</i>	369.80	363.77	361.96	367.29	354.37
<i>PB1</i>	356.85	355.95	355.25	355.18	355.74
<i>PB2</i>	357.74	356.39	355.47	355.39	355.95
<i>PB3</i>	353.50	354.58	355.21	355.15	355.72
<i>PB4</i>	361.39	356.82	354.85	354.80	355.34
<i>PB5</i>	364.15	360.90	360.27	360.20	360.67

Table A.2.10: Calculated Errors for Output Temperatures of GaAs Model (Case – 6 in Table 4.5)

Points	E_9ports	E_5ports	E_2ports	E_1port
<i>I1_1</i>	0.013091	0.015537	0.015618	0.018279
<i>I1_2</i>	0.006329	0.007258	0.007328	0.008847
<i>I1_3</i>	0.006102	0.006641	0.006718	0.007966
<i>I2_1</i>	0.012579	0.015028	0.015002	0.016903
<i>I2_2</i>	0.006158	0.007097	0.007111	0.008091
<i>I2_3</i>	0.006013	0.006542	0.006587	0.007357
<i>I3_1</i>	0.012763	0.015264	0.015368	0.017301
<i>I3_2</i>	0.006295	0.007269	0.007351	0.008393
<i>I3_3</i>	0.006163	0.006750	0.006855	0.007712
<i>I4_1</i>	0.014211	0.016983	0.018504	0.021656
<i>I4_2</i>	0.006903	0.008008	0.008958	0.010786
<i>I4_3</i>	0.006641	0.007384	0.008204	0.009675
<i>PM1</i>	0.074682	0.083665	0.119210	0.289619
<i>PM2</i>	0.077823	0.087771	0.189585	0.344646
<i>PM3</i>	0.123045	0.124143	0.040878	0.224691
<i>PM4</i>	0.086390	0.112321	0.035960	0.221060
<i>PB1</i>	0.015831	0.028144	0.029376	0.019525
<i>PB2</i>	0.023381	0.039314	0.040700	0.031001
<i>PB3</i>	0.020187	0.031963	0.030841	0.041495
<i>PB4</i>	0.074442	0.106532	0.107346	0.098550
<i>PB5</i>	0.050663	0.060483	0.061574	0.054248

A.3 Package Model

**Table A.3.1: Output Temperatures and Corresponding Errors of Package Model
(Case – 1 in Table 4.9)**

Point	T_detail	T_3ports	E_3ports	T_2ports	E_2ports	T_1port	E_1port
	(K)	(K)		(K)		(K)	
S1	328.40	327.32	0.038028	327.47	0.032746	327.50	0.031690
S2	329.36	327.98	0.047003	328.01	0.045981	328.03	0.045300
S3	329.72	328.13	0.053499	328.12	0.053836	328.13	0.053499
S4	329.26	327.93	0.045455	327.97	0.044087	327.99	0.043404
S5	328.22	327.17	0.037208	327.33	0.031538	327.36	0.030475
S6	328.47	327.50	0.034071	327.55	0.032315	327.57	0.031612
S7	329.98	328.92	0.035357	328.22	0.058706	328.18	0.060040
S8	330.67	329.25	0.046299	328.48	0.071405	328.30	0.077274
S9	329.79	328.83	0.032226	328.17	0.054381	328.14	0.055388
S10	328.22	327.29	0.032955	327.38	0.029766	327.40	0.029057
S11	327.80	327.19	0.021942	327.22	0.020863	327.23	0.020504
S12	329.64	328.83	0.027328	328.07	0.052969	327.93	0.057692
S13	330.55	329.75	0.026187	329.06	0.048773	328.07	0.081178
S14	329.40	328.70	0.023810	327.97	0.048639	327.89	0.051361
S15	327.53	326.95	0.021068	327.02	0.018525	327.03	0.018162
S16	326.16	326.39	0.008792	326.46	0.011468	326.48	0.012232
S17	327.63	327.90	0.009772	327.28	0.012667	327.27	0.013029
S18	328.25	328.19	0.002124	327.49	0.026903	327.41	0.029735
S19	327.46	327.81	0.012746	327.22	0.008740	327.22	0.008740
S20	325.90	326.13	0.008880	326.23	0.012741	326.25	0.013514
S21	323.59	324.39	0.033913	324.55	0.040695	324.58	0.041967
S22	324.62	325.26	0.025995	325.35	0.029651	325.38	0.030869
S23	324.99	325.44	0.018007	325.51	0.020808	325.53	0.021609
S24	324.52	325.20	0.027732	325.30	0.031811	325.32	0.032626
S25	323.38	324.16	0.033362	324.32	0.040205	324.34	0.041061
P1	339.99	339.13	0.021505	338.76	0.030758	338.58	0.035259
P2	341.63	340.74	0.021379	340.35	0.030747	340.13	0.036032
P3	341.63	340.74	0.021379	340.35	0.030747	340.13	0.036032
P4	339.99	339.13	0.021505	338.76	0.030758	338.58	0.035259
P5	341.51	340.74	0.018550	340.35	0.027945	340.13	0.033245
P6	346.04	345.25	0.017159	344.83	0.026281	344.56	0.032146
P7	346.04	345.25	0.017159	344.83	0.026281	344.56	0.032146
P8	341.51	340.74	0.018550	340.35	0.027945	340.13	0.033245
P9	341.36	340.74	0.014990	340.35	0.024420	340.13	0.029739
P10	345.89	345.25	0.013946	344.83	0.023099	344.56	0.028982
P11	345.89	345.25	0.013946	344.83	0.023099	344.56	0.028982
P12	341.36	340.74	0.014990	340.35	0.024420	340.13	0.029739
P13	339.60	339.13	0.011869	338.76	0.021212	338.58	0.025758
P14	341.24	340.74	0.012124	340.35	0.021581	340.13	0.026916

<i>P15</i>	341.24	340.74	0.012124	340.35	0.021581	340.13	0.026916
<i>P16</i>	339.60	339.13	0.011869	338.76	0.021212	338.58	0.025758

**Table A.3.2: Output Temperatures and Corresponding Errors of Package Model
(Case – 2 in Table 4.9)**

Point	T_detail (K)	T_3ports (K)	E_3ports	T_2ports (K)	E_2ports	T_1port (K)	E_1port
<i>S1</i>	303.86	304.03	0.044041	304.21	0.090674	304.25	0.101036
<i>S2</i>	304.51	304.52	0.002217	304.61	0.022173	304.65	0.031042
<i>S3</i>	304.78	304.62	0.033473	304.67	0.023013	304.70	0.016736
<i>S4</i>	304.44	304.49	0.011261	304.59	0.033784	304.63	0.042793
<i>S5</i>	303.73	303.90	0.045576	304.08	0.093834	304.12	0.104558
<i>S6</i>	304.46	304.46	0.000000	304.57	0.024664	304.61	0.033632
<i>S7</i>	305.63	305.56	0.012433	305.06	0.101243	305.04	0.104796
<i>S8</i>	306.22	305.80	0.067524	305.24	0.157556	305.11	0.178457
<i>S9</i>	305.47	305.49	0.003656	305.02	0.082267	305.02	0.082267
<i>S10</i>	304.28	304.29	0.002336	304.43	0.035047	304.47	0.044393
<i>S11</i>	304.69	304.54	0.031983	304.62	0.014925	304.66	0.006397
<i>S12</i>	306.12	305.74	0.062092	305.20	0.150327	305.10	0.166667
<i>S13</i>	306.91	306.53	0.054993	306.05	0.124457	305.16	0.253256
<i>S14</i>	305.92	305.65	0.045608	305.13	0.133446	305.07	0.143581
<i>S15</i>	304.49	304.36	0.028953	304.48	0.002227	304.52	0.006682
<i>S16</i>	304.34	304.40	0.013825	304.52	0.041475	304.56	0.050691
<i>S17</i>	305.35	305.42	0.013084	304.99	0.067290	305.00	0.065421
<i>S18</i>	305.84	305.60	0.041096	305.11	0.125000	305.06	0.133562
<i>S19</i>	305.23	305.36	0.024857	304.96	0.051625	304.97	0.049713
<i>S20</i>	304.17	304.24	0.016787	304.38	0.05036	304.42	0.059952
<i>S21</i>	303.60	303.77	0.047222	303.95	0.097222	303.99	0.108333
<i>S22</i>	304.16	304.19	0.007212	304.33	0.040865	304.37	0.050481
<i>S23</i>	304.39	304.27	0.027335	304.39	0.000000	304.43	0.009112
<i>S24</i>	304.11	304.16	0.012165	304.31	0.048662	304.35	0.058394
<i>S25</i>	303.49	303.65	0.045845	303.83	0.097421	303.87	0.108883
<i>P1</i>	316.70	316.48	0.013174	316.24	0.027545	316.09	0.036527
<i>P2</i>	318.32	318.09	0.012555	317.83	0.026747	317.65	0.036572
<i>P3</i>	318.32	318.09	0.012555	317.83	0.026747	317.65	0.036572
<i>P4</i>	316.70	316.48	0.013174	316.24	0.027545	316.09	0.036527
<i>P5</i>	318.32	318.09	0.012555	317.82	0.027293	317.64	0.037118
<i>P6</i>	322.84	322.59	0.010946	322.30	0.023643	322.08	0.033275
<i>P7</i>	322.84	322.59	0.010946	322.30	0.023643	322.08	0.033275
<i>P8</i>	318.32	318.09	0.012555	317.82	0.027293	317.64	0.037118
<i>P9</i>	318.32	318.09	0.012555	317.82	0.027293	317.64	0.037118
<i>P10</i>	322.84	322.59	0.010946	322.30	0.023643	322.08	0.033275
<i>P11</i>	322.84	322.59	0.010946	322.30	0.023643	322.08	0.033275
<i>P12</i>	318.32	318.09	0.012555	317.82	0.027293	317.64	0.037118

<i>P13</i>	316.70	316.48	0.013174	316.24	0.027545	316.09	0.036527
<i>P14</i>	318.32	318.09	0.012555	317.83	0.026747	317.65	0.036572
<i>P15</i>	318.32	318.09	0.012555	317.83	0.026747	317.65	0.036572
<i>P16</i>	316.70	316.48	0.013174	316.24	0.027545	316.09	0.036527

**Table A.3.3: Output Temperatures and Corresponding Errors of Package Model
(Case – 3 in Table 4.9)**

Point	T_detail (K)	T_3ports (K)	E_3ports	T_2ports (K)	E_2ports	T_1port (K)	E_1port
<i>S1</i>	301.79	301.83	0.022346	301.94	0.083799	302.00	0.117318
<i>S2</i>	301.98	301.91	0.035354	301.99	0.005051	302.04	0.030303
<i>S3</i>	302.07	301.94	0.062802	302.00	0.033816	302.04	0.014493
<i>S4</i>	301.95	301.91	0.020513	301.98	0.015385	302.03	0.041026
<i>S5</i>	301.77	301.82	0.028249	301.93	0.090395	301.99	0.124294
<i>S6</i>	301.91	301.87	0.020942	301.95	0.020942	302.00	0.047120
<i>S7</i>	302.28	302.22	0.026316	302.02	0.114035	302.05	0.100877
<i>S8</i>	302.50	302.30	0.080000	302.08	0.168000	302.06	0.176000
<i>S9</i>	302.22	302.19	0.013514	302.01	0.094595	302.04	0.081081
<i>S10</i>	301.87	301.85	0.010695	301.94	0.037433	301.99	0.064171
<i>S11</i>	301.92	301.86	0.031250	301.93	0.005208	301.98	0.03125
<i>S12</i>	302.40	302.26	0.058333	302.04	0.150000	302.03	0.154167
<i>S13</i>	302.73	302.59	0.051282	302.40	0.120879	302.04	0.252747
<i>S14</i>	302.32	302.22	0.043103	302.02	0.129310	302.03	0.125000
<i>S15</i>	301.87	301.83	0.021390	301.92	0.026738	301.96	0.048128
<i>S16</i>	301.73	301.79	0.034682	301.87	0.080925	301.92	0.109827
<i>S17</i>	302.05	302.11	0.029268	301.95	0.04878	301.98	0.034146
<i>S18</i>	302.23	302.18	0.022422	301.98	0.112108	301.99	0.107623
<i>S19</i>	302.00	302.09	0.045000	301.94	0.030000	301.98	0.010000
<i>S20</i>	301.69	301.76	0.041420	301.86	0.100592	301.91	0.130178
<i>S21</i>	301.46	301.62	0.109589	301.74	0.191781	301.79	0.226027
<i>S22</i>	301.63	301.71	0.049080	301.80	0.104294	301.84	0.128834
<i>S23</i>	301.70	301.73	0.017647	301.81	0.064706	301.85	0.088235
<i>S24</i>	301.60	301.70	0.062500	301.79	0.118750	301.84	0.150000
<i>S25</i>	301.43	301.61	0.125874	301.72	0.202797	301.77	0.237762
<i>P1</i>	301.17	301.16	0.008547	301.13	0.034188	301.12	0.042735
<i>P2</i>	302.26	302.23	0.013274	302.20	0.026549	302.19	0.030973
<i>P3</i>	302.26	302.23	0.013274	302.20	0.026549	302.19	0.030973
<i>P4</i>	301.17	301.16	0.008547	301.13	0.034188	301.12	0.042735
<i>P5</i>	302.26	302.23	0.013274	302.20	0.026549	302.19	0.030973
<i>P6</i>	305.93	305.90	0.005059	305.87	0.010118	305.84	0.015177
<i>P7</i>	305.93	305.90	0.005059	305.87	0.010118	305.84	0.015177
<i>P8</i>	302.26	302.23	0.013274	302.20	0.026549	302.19	0.030973
<i>P9</i>	302.25	302.23	0.008889	302.20	0.022222	302.19	0.026667
<i>P10</i>	305.93	305.90	0.005059	305.87	0.010118	305.84	0.015177

<i>P11</i>	305.93	305.90	0.005059	305.87	0.010118	305.84	0.015177
<i>P12</i>	302.25	302.23	0.008889	302.20	0.022222	302.19	0.026667
<i>P13</i>	301.17	301.16	0.008547	301.13	0.034188	301.12	0.042735
<i>P14</i>	302.25	302.23	0.008889	302.20	0.022222	302.19	0.026667
<i>P15</i>	302.25	302.23	0.008889	302.20	0.022222	302.19	0.026667
<i>P16</i>	301.17	301.16	0.008547	301.13	0.034188	301.12	0.042735

**Table A.3.4: Output Temperatures and Corresponding Errors of Package Model
(Case – 4 in Table 4.9)**

Point	T_detail (K)	T_3ports (K)	E_3ports	T_2ports (K)	E_2ports	T_1port (K)	E_1port
<i>S1</i>	300.47	300.56	0.191489	300.66	0.404255	300.69	0.468085
<i>S2</i>	300.67	300.67	0.000000	300.73	0.089552	300.76	0.134328
<i>S3</i>	300.76	300.70	0.078947	300.74	0.026316	300.77	0.013158
<i>S4</i>	300.65	300.66	0.015385	300.72	0.107692	300.75	0.153846
<i>S5</i>	300.45	300.54	0.200000	300.64	0.422222	300.67	0.488889
<i>S6</i>	300.66	300.65	0.015152	300.72	0.090909	300.75	0.136364
<i>S7</i>	301.05	301.03	0.019048	300.81	0.228571	300.82	0.219048
<i>S8</i>	301.29	301.12	0.131783	300.88	0.317829	300.83	0.356589
<i>S9</i>	300.99	301.00	0.010101	300.80	0.191919	300.82	0.171717
<i>S10</i>	300.61	300.62	0.016393	300.70	0.147541	300.73	0.196721
<i>S11</i>	300.73	300.67	0.082192	300.73	0.000000	300.76	0.041096
<i>S12</i>	301.25	301.10	0.120000	300.86	0.312000	300.83	0.336000
<i>S13</i>	301.60	301.45	0.093750	301.25	0.218750	300.84	0.475000
<i>S14</i>	301.17	301.06	0.094017	300.84	0.282051	300.83	0.290598
<i>S15</i>	300.68	300.64	0.058824	300.71	0.044118	300.74	0.088235
<i>S16</i>	300.61	300.64	0.049180	300.71	0.163934	300.74	0.213115
<i>S17</i>	300.95	300.98	0.031579	300.80	0.157895	300.82	0.136842
<i>S18</i>	301.14	301.04	0.087719	300.83	0.271930	300.83	0.271930
<i>S19</i>	300.90	300.96	0.066667	300.79	0.122222	300.81	0.100000
<i>S20</i>	300.57	300.61	0.070175	300.69	0.210526	300.72	0.263158
<i>S21</i>	300.42	300.52	0.238095	300.62	0.476190	300.65	0.547619
<i>S22</i>	300.58	300.60	0.034483	300.68	0.172414	300.71	0.224138
<i>S23</i>	300.66	300.62	0.060606	300.69	0.045455	300.72	0.090909
<i>S24</i>	300.56	300.60	0.071429	300.68	0.214286	300.71	0.267857
<i>S25</i>	300.40	300.50	0.250000	300.69	0.500000	300.63	0.575000
<i>P1</i>	301.06	301.05	0.009434	301.02	0.037736	301.01	0.047170
<i>P2</i>	302.14	302.12	0.009346	302.08	0.028037	302.07	0.032710
<i>P3</i>	302.14	302.12	0.009346	302.08	0.028037	302.07	0.032710
<i>P4</i>	301.06	301.05	0.009434	301.02	0.037736	301.01	0.047170
<i>P5</i>	302.14	302.12	0.009346	302.08	0.028037	302.07	0.032710
<i>P6</i>	305.81	305.78	0.005164	305.74	0.012048	305.71	0.017212
<i>P7</i>	305.81	305.78	0.005164	305.74	0.012048	305.71	0.017212
<i>P8</i>	302.14	302.12	0.009346	302.08	0.028037	302.07	0.032710

<i>P9</i>	302.14	302.12	0.009346	302.08	0.028037	302.07	0.032710
<i>P10</i>	305.81	305.78	0.005164	305.74	0.012048	305.71	0.017212
<i>P11</i>	305.81	305.78	0.005164	305.74	0.012048	305.71	0.017212
<i>P12</i>	302.14	302.12	0.009346	302.08	0.028037	302.07	0.032710
<i>P13</i>	301.06	301.05	0.009434	301.02	0.037736	301.01	0.047170
<i>P14</i>	302.14	302.12	0.009346	302.08	0.028037	302.07	0.032710
<i>P15</i>	302.14	302.12	0.009346	302.08	0.028037	302.07	0.032710
<i>P16</i>	301.06	301.05	0.009434	301.02	0.037736	301.01	0.047170

**Table A.3.5: Output Temperatures and Corresponding Errors of Package Model
(Case – 6 in Table 4.9)**

Point	T_detail (K)	T_3ports (K)	E_3ports	T_2ports (K)	E_2ports	T_1port (K)	E_1port
<i>S1</i>	300.48	300.57	0.187500	300.67	0.395833	300.71	0.479167
<i>S2</i>	300.68	300.68	0.000000	300.74	0.088235	300.77	0.132353
<i>S3</i>	300.78	300.71	0.089744	300.75	0.038462	300.78	0.000000
<i>S4</i>	300.66	300.67	0.015152	300.73	0.106061	300.77	0.166667
<i>S5</i>	300.45	300.55	0.222222	300.65	0.444444	300.68	0.511111
<i>S6</i>	300.67	300.67	0.000000	300.73	0.089552	300.76	0.134328
<i>S7</i>	301.07	301.05	0.018692	300.83	0.224299	300.84	0.214953
<i>S8</i>	301.31	301.14	0.129771	300.90	0.312977	300.85	0.351145
<i>S9</i>	301.01	301.02	0.009901	300.82	0.188119	300.83	0.178218
<i>S10</i>	300.62	300.63	0.016129	300.71	0.145161	300.74	0.193548
<i>S11</i>	300.75	300.69	0.080000	300.74	0.013333	300.77	0.026667
<i>S12</i>	301.27	301.12	0.118110	300.88	0.307087	300.85	0.330709
<i>S13</i>	301.63	301.47	0.098160	301.27	0.220859	300.86	0.472393
<i>S14</i>	301.19	301.08	0.092437	300.85	0.285714	300.84	0.294118
<i>S15</i>	300.69	300.65	0.057971	300.72	0.043478	300.75	0.086957
<i>S16</i>	300.63	300.65	0.031746	300.72	0.142857	300.76	0.206349
<i>S17</i>	300.96	301.00	0.041667	300.81	0.156250	300.83	0.135417
<i>S18</i>	301.15	301.06	0.078261	300.85	0.260870	300.84	0.269565
<i>S19</i>	300.92	300.98	0.065217	300.80	0.130435	300.83	0.097826
<i>S20</i>	300.58	300.62	0.068966	300.70	0.206897	300.73	0.258621
<i>S21</i>	300.43	300.53	0.232558	300.63	0.465116	300.66	0.534884
<i>S22</i>	300.60	300.61	0.016667	300.69	0.150000	300.72	0.200000
<i>S23</i>	300.67	300.63	0.059701	300.70	0.044776	300.73	0.089552
<i>S24</i>	300.57	300.61	0.070175	300.69	0.210526	300.72	0.263158
<i>S25</i>	300.41	300.51	0.243902	300.61	0.487805	300.64	0.560976
<i>P1</i>	301.12	301.10	0.017857	301.07	0.044643	301.06	0.053571
<i>P2</i>	302.23	302.21	0.008969	302.18	0.022422	302.16	0.031390
<i>P3</i>	302.23	302.21	0.008969	302.18	0.022422	302.16	0.031390
<i>P4</i>	301.12	301.10	0.017857	301.07	0.044643	301.06	0.053571
<i>P5</i>	302.23	302.21	0.008969	302.18	0.022422	302.16	0.031390
<i>P6</i>	305.98	305.95	0.005017	305.91	0.011706	305.88	0.016722

<i>P7</i>	305.98	305.95	0.005017	305.91	0.011706	305.88	0.016722
<i>P8</i>	302.23	302.21	0.008969	302.18	0.022422	302.16	0.031390
<i>P9</i>	302.23	302.21	0.008969	302.18	0.022422	302.16	0.031390
<i>P10</i>	305.98	305.95	0.005017	305.91	0.011706	305.88	0.016722
<i>P11</i>	305.98	305.95	0.005017	305.91	0.011706	305.88	0.016722
<i>P12</i>	302.23	302.21	0.008969	302.18	0.022422	302.16	0.031390
<i>P13</i>	301.12	301.10	0.017857	301.07	0.044643	301.06	0.053571
<i>P14</i>	302.23	302.21	0.008969	302.18	0.022422	302.16	0.031390
<i>P15</i>	302.23	302.21	0.008969	302.18	0.022422	302.16	0.031390
<i>P16</i>	301.12	301.10	0.017857	301.07	0.044643	301.06	0.053571

Appendix B

Neural Network Modeling Results

B.1 GaN Based Power Package Amplifier

Table B.1.1: Testing Errors of GaN Model with Four-Layer Perceptrons and Four-Port Configuration

Output	Average Error (BP4)	Maximum Error (BP4)	Average Error (CG4)	Maximum Error (CG4)
<i>T-linear</i>	2.41494270	20.0477350	2.74927880	21.1156850
<i>T-nonlinear</i>	2.65020900	18.2094290	2.97454670	19.2585770
<i>T-bot</i>	0.94954900	3.7385294	2.44730760	8.3350440
<i>TM1</i>	11.84090300	27.8511410	11.87790800	27.8989430
<i>TM2</i>	11.76631600	28.5727310	11.39116200	30.6001680
<i>TM3</i>	1.95915210	8.4325040	1.89793680	7.8421397
<i>I1-1</i>	0.55015240	3.5540729	0.71823370	5.2614713
<i>I1-2</i>	0.82111520	3.2995460	0.92921525	4.9944067
<i>I1-3</i>	1.12536860	3.8178330	1.20561900	5.4506120
<i>I1-4</i>	0.77888000	3.6058020	0.93492573	5.7536700
<i>I1-5</i>	0.79244184	2.9692955	0.90955615	4.8699190
<i>I1-6</i>	1.29211710	4.0354857	1.36314680	5.9223000
<i>I2-1</i>	1.14966820	4.2125044	1.27807100	6.4492683
<i>I2-2</i>	0.73016196	2.8608134	0.86132700	4.7709904
<i>I2-3</i>	1.54429610	4.8665504	1.59063300	6.3749814
<i>I2-4</i>	1.08311500	4.0398355	1.21692650	6.3140440
<i>I2-5</i>	0.71082410	2.8319552	0.84514105	4.7983130
<i>I2-6</i>	1.37532290	4.3464127	1.43168400	6.0881110
<i>I3-1</i>	0.71708393	3.4185455	0.88327280	5.6088140
<i>I3-2</i>	0.85064775	3.0549430	0.95585470	4.9841300
<i>I3-3</i>	1.11937710	3.6118440	1.19530930	5.4427986
<i>I3-4</i>	0.55984664	3.4678640	0.72927964	5.2841650
<i>I3-5</i>	0.87061197	3.3997302	0.96980494	5.1098290
<i>I3-6</i>	1.05676910	3.8432431	1.12704460	5.2571970

<i>PM1</i>	22.1079180	50.7927470	22.10477300	50.4745980
<i>PM2</i>	26.0629180	63.4717700	25.22136100	66.6689400
<i>PM3</i>	1.2235150	6.7541830	5.64201160	19.0049860
<i>PB1</i>	1.3535178	7.2056375	1.23957540	6.2986856
<i>PB2</i>	2.0426793	8.5403000	1.89845920	7.4756690
<i>PB3</i>	1.3529834	7.2141604	1.24716650	6.4967990
<i>PB4</i>	1.7862096	8.3772350	1.65786610	7.3197374
<i>P1</i>	0.8424973	3.3342156	0.94690907	4.9791230
<i>P2</i>	0.8154406	3.0321610	0.92898190	4.8494220
<i>P3</i>	0.7564825	2.9488292	0.88277006	4.7466050
<i>P4</i>	0.7379744	2.9195542	0.86651890	4.7765430
<i>P5</i>	0.8710570	3.0985190	0.97342100	4.9700994
<i>P6</i>	0.8895933	3.4330437	0.98566705	5.0985017
<i>P7</i>	1.5432045	6.0184474	1.54196320	6.8637147
<i>P8</i>	2.3006756	7.1425050	2.31404570	8.1457290
<i>P9</i>	3.3399673	9.3369130	3.36002420	9.8615800
<i>P10</i>	2.8951232	8.1873820	2.93542900	9.1361010
<i>P11</i>	2.0703588	6.6060624	2.09078030	7.7820625
<i>P12</i>	1.1547043	4.9673710	1.19888730	6.2476754

Table B.1.2: Testing Errors of GaN Model with Four-Layer Perceptrons & Five-Port Configuration

Output	Average Error (BP4)	Maximum Error (BP4)	Average Error (CG4)	Maximum Error (CG4)
<i>T-linear</i>	2.17259170	10.4746650	3.36802740	15.3559350
<i>T-nonlinear</i>	2.23280050	6.8196445	2.73128370	9.7784440
<i>TP1</i>	15.68848500	47.4356460	10.15829850	28.7971420
<i>TP2</i>	16.12359000	54.4901540	16.96480000	54.7249450
<i>TP3</i>	16.11911600	50.5476400	15.47529000	46.2334900
<i>TP4</i>	15.64284800	48.9603300	15.95302500	46.5533180
<i>TP5</i>	15.56838600	52.6432270	14.28571800	49.8728070
<i>II-1</i>	1.46619470	4.5749187	1.29440140	4.0734740
<i>II-2</i>	1.22218610	4.3127890	0.88989896	3.4562707
<i>II-3</i>	1.62009690	4.0859175	1.28243770	4.0851064
<i>II-4</i>	1.06415340	2.9429991	0.92463225	3.2941809
<i>II-5</i>	0.90999925	3.3210523	0.72675460	2.7610285
<i>II-6</i>	1.18584600	3.2591925	1.02044560	3.2749126
<i>I2-1</i>	0.60871905	1.7220162	0.48107030	2.2384927
<i>I2-2</i>	0.54866390	1.8449856	0.49301913	1.7890356
<i>I2-3</i>	0.72768843	2.6961780	0.69435316	2.4959285
<i>I2-4</i>	0.71020940	2.1779760	0.62730306	2.5150812
<i>I2-5</i>	0.46779700	1.8975588	0.50385070	1.9993135
<i>I2-6</i>	0.85374230	2.7876210	0.78158400	2.5681038
<i>I3-1</i>	1.12040750	3.1508274	1.06948580	3.7246535
<i>I3-2</i>	0.68799590	2.9099405	0.74499416	3.2217060
<i>I3-3</i>	1.23644240	3.2575107	1.17494920	3.6941495
<i>I3-4</i>	1.42150500	3.9602976	1.37938010	4.4670315
<i>I3-5</i>	0.90723044	3.6529431	0.95050800	4.0303874
<i>I3-6</i>	1.53699760	4.0735180	1.49121930	4.6010056
<i>PM1</i>	3.19889070	10.5147660	2.02670980	6.2983740
<i>PM2</i>	3.66192530	11.7894600	2.36231760	6.7698207
<i>PM3</i>	4.26113270	13.7086100	2.74282240	7.8856044
<i>PB1</i>	2.84373550	7.6566670	2.61803960	7.5139090
<i>PB2</i>	3.08080940	8.2615140	2.11776450	6.4456644
<i>PB3</i>	2.91596560	7.5821195	2.79714350	8.5284150
<i>PB4</i>	3.19786520	8.6553660	3.15176000	7.9516654
<i>P1</i>	1.23602460	4.2311673	0.88987750	3.4273713
<i>P2</i>	0.92473406	3.2749430	0.73280185	2.7381775
<i>P3</i>	0.56838936	1.8609947	0.50652117	1.8394618
<i>P4</i>	0.48314282	1.9559169	0.51565546	2.0566500
<i>P5</i>	0.69871450	2.9667760	0.75307447	3.2853363
<i>P6</i>	0.91390866	3.7119002	0.95726687	4.0995740
<i>P7</i>	1.70691470	4.3119802	1.45258980	4.3540440
<i>P8</i>	1.31731240	3.3096933	1.05085900	3.3261073
<i>P9</i>	0.95425140	3.1144874	0.63327070	2.1721065
<i>P10</i>	1.00033970	3.5282270	0.78455186	3.2008817
<i>P11</i>	1.38839880	4.0384936	1.26517620	4.3716360
<i>P12</i>	1.64607920	4.6116510	1.56268850	5.0012390

B.2 GaAs Based Power Amplifier

Table B.2.1: Testing Errors of GaAs Model with Four-Layer Perceptrons and Five-Port Configuration

Output	Average Error (BP4)	Maximum Error (BP4)	Average Error (CG4)	Maximum Error (CG4)
<i>T-linear</i>	3.14161100	12.7752970	2.8381526	12.8778640
<i>T-nonlinear</i>	3.22117140	12.9597150	3.0847550	11.9766290
<i>TP1</i>	2.23572500	8.1451520	1.9249161	7.1759305
<i>TP2</i>	12.99845300	28.7106420	7.9454346	26.8586600
<i>TP3</i>	13.16460800	29.6669730	13.0863490	30.9459340
<i>TP4</i>	2.40119120	7.3238125	10.7506270	33.1121940
<i>TP5</i>	11.97915200	28.4870300	12.1319820	27.7803970
<i>I1-1</i>	0.96100026	3.2966511	1.3153844	4.6668644
<i>I1-2</i>	0.61649360	2.1245070	1.1982026	3.3512020
<i>I1-3</i>	0.60789880	2.1346533	1.1922393	3.4988377
<i>I2-1</i>	0.74553720	2.6928590	1.1915933	3.9145155
<i>I2-2</i>	0.60211325	2.3265480	1.2062361	3.7471542
<i>I2-3</i>	0.59751326	2.2369206	1.1994054	3.7606764
<i>I3-1</i>	0.74498590	2.7463020	1.1856592	3.7589402
<i>I3-2</i>	0.58735293	2.1959739	1.2184523	3.8083947
<i>I3-3</i>	0.58047634	2.1017864	1.2094997	3.8660808
<i>I4-1</i>	1.12255480	3.7394803	1.2359029	4.6055670
<i>I4-2</i>	0.61403920	2.2267058	1.2881348	4.5757550
<i>I4-3</i>	0.58971780	2.0164473	1.2641913	4.5097460
<i>PM1</i>	23.86480300	49.6680100	23.5712130	54.7804450
<i>PM2</i>	23.90364800	50.5984400	13.8245000	45.5214730
<i>PM3</i>	23.72596000	55.1201900	23.9918960	53.4846700
<i>PM4</i>	4.40305470	10.91938900	17.8149950	53.6402100
<i>PB1</i>	2.14039470	7.76017900	1.9898176	6.7918990
<i>PB2</i>	2.13810940	7.77460240	1.9624932	6.5614830
<i>PB3</i>	2.13170770	7.72975540	1.9806156	6.7077427
<i>PB4</i>	2.13170770	7.72975540	1.9806156	6.7077427
<i>PB5</i>	2.11726570	7.79395150	1.9517250	6.6710534

B.3 Package Model

Table B.3.1: Testing Errors of Package Model with Four-Layer Perceptrons and Three-Port Configuration

Output	Average Error (BP4)	Maximum Error (BP4)	Average Error (CG4)	Maximum Error (CG4)
<i>T-linear</i>	6.08212500	20.5837300	5.9765690	20.2582700
<i>T-nonlinear</i>	5.93204900	19.9994100	5.7717090	20.3551400
<i>T-alpha</i>	3.90680000	12.2270500	3.4117790	13.0916800
<i>TP1</i>	3.49536700	12.2769100	3.7540260	13.2647700
<i>TP2</i>	2.85086900	9.0309170	2.8355440	9.9687490
<i>TP3</i>	9.58026700	26.2361700	10.0311200	28.0604300
<i>P1</i>	1.55512600	6.8407360	1.8787410	8.1925670
<i>P2</i>	0.63569500	3.4298500	1.3152470	5.7767620
<i>P3</i>	0.63569500	3.4298500	1.3152430	5.7766990
<i>P4</i>	1.55512600	6.8407360	1.8787410	8.1925670
<i>P5</i>	0.63617000	3.4321910	1.3153960	5.7784450
<i>P6</i>	2.60626300	9.6395660	2.8474950	8.8371390
<i>P7</i>	2.60625800	9.6395150	2.8474980	8.8371390
<i>P8</i>	0.63614500	3.4320650	1.3153970	5.7784450
<i>P9</i>	0.63614500	3.4320650	1.3153960	5.7784450
<i>P10</i>	2.60625500	9.6395150	2.8474950	8.8371390
<i>P11</i>	2.60625800	9.6395150	2.8474950	8.8371390
<i>P12</i>	0.63614400	3.4320650	1.3153970	5.7784450
<i>P13</i>	1.55512600	6.8407360	1.8787414	8.1925670
<i>P14</i>	0.63569325	3.4298500	1.3152477	5.7767615
<i>P15</i>	0.63571980	3.4299757	1.3152477	5.7767615
<i>P16</i>	1.55512640	6.840736	1.8787410	8.1925670

Appendix C

Iteration Results

C.1 GaN Based Power Package Amplifier

Table C.1.1: Output Temperatures for Detailed and Sub-models 3 and 4 and Corresponding Errors of GaN Model with Four-Port Configuration

Output	Model-3			Model-4		
	T _{full}	T _{sub}	Error	T _{full}	T _{sub}	Error
	(K)	(K)		(K)	(K)	
<i>T-max</i>	401.270520	403.1878	0.018932	401.444803	403.4073	0.019345
<i>I1-1</i>	372.042118	374.2411	0.030524	376.295085	374.4163	0.024625
<i>I1-2</i>	376.208840	381.4057	0.068192	380.456404	381.5867	0.014049
<i>I1-3</i>	372.640068	375.4317	0.038431	376.698848	375.6148	0.014134
<i>I1-4</i>	376.247013	377.8282	0.020738	376.427219	378.0137	0.020758
<i>I1-5</i>	381.922821	386.5248	0.056175	382.103078	386.7191	0.056222
<i>I1-6</i>	377.075942	379.1942	0.027483	377.248923	379.3813	0.027604
<i>I2-1</i>	381.709384	378.7106	0.036701	381.886776	378.8956	0.036528
<i>I2-2</i>	387.937108	388.4081	0.005356	388.114267	388.6069	0.005591
<i>I2-3</i>	382.292999	379.9113	0.028942	382.462221	380.0875	0.028798
<i>I2-4</i>	382.061111	379.7025	0.028742	382.233366	379.8846	0.028562
<i>I2-5</i>	388.322290	386.4126	0.021622	388.494058	386.6010	0.021392
<i>I2-6</i>	382.735802	379.9765	0.033351	382.900077	380.1559	0.033102
<i>I3-1</i>	381.264865	378.5138	0.033853	377.666157	378.6947	0.013243
<i>I3-2</i>	387.010081	386.7947	0.002475	383.576467	386.9750	0.040664
<i>I3-3</i>	381.873262	380.1200	0.021414	378.533109	380.3088	0.022611
<i>I3-4</i>	374.743101	376.5119	0.023665	378.476178	376.6862	0.022809
<i>I3-5</i>	379.525686	380.7002	0.014769	383.043983	380.8832	0.026020
<i>I3-6</i>	375.225896	376.0348	0.010753	378.683492	376.2053	0.031496

Table C.1.2: Output Temperatures for Detailed and Sub-models 5 and 6 and Corresponding Errors of GaN Model with Four-Port Configuration

Output	Model-5			Model-6		
	T _{full} (K)	T _{sub} (K)	Error	T _{full} (K)	T _{sub} (K)	Error
<i>T-max</i>	401.424425	403.3787	0.019268	401.110493	403.0060	0.018747
<i>I1-1</i>	376.279220	374.3940	0.024715	371.949263	374.1022	0.029923
<i>I1-2</i>	380.442193	381.5630	0.013933	376.115668	381.2574	0.067552
<i>I1-3</i>	376.687603	375.5914	0.014294	372.542489	375.2812	0.037753
<i>I1-4</i>	380.343760	377.9898	0.029299	380.071092	377.6802	0.029860
<i>I1-5</i>	385.948666	386.6942	0.008674	385.672732	386.3695	0.008133
<i>I1-6</i>	380.921802	379.3579	0.019326	380.646190	379.0386	0.019934
<i>I2-1</i>	377.976008	378.8720	0.011491	377.699037	378.5631	0.011121
<i>I2-2</i>	384.314442	388.5814	0.050608	384.033349	388.2450	0.050119
<i>I2-3</i>	378.834872	380.0660	0.015617	378.554440	379.7632	0.015388
<i>I2-4</i>	382.208322	379.8611	0.028552	381.920442	379.5563	0.028859
<i>I2-5</i>	388.470114	386.5764	0.021405	388.177785	386.2585	0.021766
<i>I2-6</i>	382.880011	380.1330	0.033144	382.588960	379.8259	0.033456
<i>I3-1</i>	377.637773	378.6715	0.013315	381.110204	378.3686	0.033801
<i>I3-2</i>	383.548889	386.9515	0.040726	386.850874	386.6460	0.002359
<i>I3-3</i>	378.509079	380.2845	0.022614	381.712504	379.9621	0.021421
<i>I3-4</i>	378.444098	376.6634	0.022700	374.581065	376.3708	0.023997
<i>I3-5</i>	383.012522	380.8597	0.025934	379.358863	380.5552	0.015075
<i>I3-6</i>	378.655553	376.1833	0.031431	375.057750	375.8926	0.011123

Table C.1.3: Output Temperatures for Detailed and Sub-models 7 and 8 and Corresponding Errors of GaN Model with Four-Port Configuration

Output	Model-7			Model-8		
	T _{full} (K)	T _{sub} (K)	Error	T _{full} (K)	T _{sub} (K)	Error
<i>T-max</i>	400.129321	401.8566	0.017250	396.425717	397.8427	0.014695
<i>I1-1</i>	371.101498	373.1874	0.029337	372.007359	369.8648	0.029755
<i>I1-2</i>	375.268368	380.3048	0.066913	376.161352	376.8739	0.009356
<i>I1-3</i>	371.707607	374.3179	0.036402	372.452728	370.8623	0.021951
<i>I1-4</i>	379.186365	376.7129	0.031236	375.925792	373.2340	0.035453
<i>I1-5</i>	384.784434	385.3565	0.006747	381.498365	381.7198	0.002717
<i>I1-6</i>	379.775579	378.0503	0.021627	376.539730	374.5039	0.026598
<i>I2-1</i>	380.676892	377.5983	0.038160	373.481830	374.1289	0.008806
<i>I2-2</i>	386.895966	387.2009	0.003509	379.772373	383.4707	0.046361
<i>I2-3</i>	381.269490	378.8271	0.030053	374.371938	375.4430	0.014401
<i>I2-4</i>	377.155963	378.6031	0.018756	373.730154	375.1592	0.019382
<i>I2-5</i>	383.546467	385.2686	0.020613	380.075396	381.7139	0.020462
<i>I2-6</i>	378.107177	378.8744	0.009823	374.699509	375.4492	0.010036

<i>I3-1</i>	380.161606	377.4223	0.034172	376.597098	374.0046	0.033846
<i>I3-2</i>	385.894675	385.6938	0.002339	382.283089	382.2489	0.000416
<i>I3-3</i>	380.777429	378.9637	0.022453	377.232704	375.3964	0.023776
<i>I3-4</i>	373.635369	375.4558	0.024722	373.577209	372.1417	0.019510
<i>I3-5</i>	378.406397	379.6023	0.015253	378.093188	376.1629	0.024718
<i>I3-6</i>	374.124718	374.9872	0.011636	373.821361	371.6971	0.028776

Table C.1.4: Output Temperatures for Detailed and Sub-models 3 and 4 and Corresponding Errors of GaN Model with Five-Port Configuration

Output	Model-3			Model-4		
	T full	T sub	Error	T full	T sub	Error
	(K)	(K)		(K)	(K)	
<i>T-max</i>	401.270520	405.6071	0.042822	401.444803	405.8197	0.043126
<i>I1-1</i>	372.042118	375.1492	0.043129	376.295085	375.3859	0.011917
<i>I1-2</i>	376.208840	382.2970	0.079888	380.456404	382.5333	0.025814
<i>I1-3</i>	372.640068	377.1429	0.061988	376.698848	377.4043	0.009198
<i>I1-4</i>	376.247013	379.9431	0.048475	376.427219	380.1939	0.049285
<i>I1-5</i>	381.922821	387.9782	0.073916	382.103078	388.2329	0.07466
<i>I1-6</i>	377.075942	381.0069	0.051001	377.248923	381.2554	0.051865
<i>I2-1</i>	381.709384	380.9528	0.009259	381.886776	381.2116	0.008245
<i>I2-2</i>	387.937108	389.6147	0.019077	388.114267	389.8591	0.019802
<i>I2-3</i>	382.292999	382.4265	0.001622	382.462221	382.6774	0.002609
<i>I2-4</i>	382.061111	381.6296	0.005258	382.233366	381.8748	0.004360
<i>I2-5</i>	388.322290	388.0070	0.003570	388.494058	388.2419	0.002849
<i>I2-6</i>	382.735802	381.2658	0.017767	382.900077	381.5021	0.016863
<i>I3-1</i>	381.264865	380.7821	0.005941	377.666157	381.0306	0.043319
<i>I3-2</i>	387.010081	388.3763	0.015702	383.576467	388.6067	0.060187
<i>I3-3</i>	381.873262	381.8238	0.000604	378.533109	382.0574	0.044876
<i>I3-4</i>	374.743101	378.9757	0.056629	378.476178	379.2118	0.009374
<i>I3-5</i>	379.525686	382.8621	0.041954	383.043983	383.0909	0.000565
<i>I3-6</i>	375.225896	378.7734	0.047158	378.683492	379.0105	0.004156

Table C.1.5: Output Temperatures for Detailed and Sub-models 5 and 6 and Corresponding Errors of GaN Model with Five-Port Configuration

Output	Model-5			Model-6		
	T full	T sub	Error	T full	T sub	Error
	(K)	(K)		(K)	(K)	
<i>T-max</i>	401.424425	405.7919	0.043061	401.110493	405.4359	0.042779
<i>I1-1</i>	376.279220	375.3606	0.012043	371.949263	374.9920	0.042290
<i>I1-2</i>	380.442193	382.5080	0.025681	376.115668	382.1371	0.079109
<i>I1-3</i>	376.687603	377.3777	0.008999	372.542489	376.9657	0.060974

<i>I1-4</i>	380.343760	380.1660	0.002212	380.071092	379.7692	0.003770
<i>I1-5</i>	385.948666	388.2053	0.026256	385.672732	387.8018	0.024851
<i>I1-6</i>	380.921802	381.2289	0.003795	380.646190	380.8294	0.002272
<i>I2-1</i>	377.976008	381.1800	0.041089	377.699037	380.7605	0.039402
<i>I2-2</i>	384.314442	389.8290	0.065405	384.033349	389.4290	0.064208
<i>I2-3</i>	378.834872	382.6479	0.048367	378.554440	382.2332	0.046831
<i>I2-4</i>	382.208322	381.8409	0.004469	381.920442	381.4275	0.006017
<i>I2-5</i>	388.470114	388.2095	0.002946	388.177785	387.8108	0.004162
<i>I2-6</i>	382.880011	381.4712	0.016998	382.588960	381.0697	0.018395
<i>I3-1</i>	377.637773	380.9933	0.043220	381.110204	380.5686	0.006677
<i>I3-2</i>	383.548889	388.5713	0.060113	386.850874	388.1677	0.015162
<i>I3-3</i>	378.509079	382.0235	0.044765	381.712504	381.6144	0.001201
<i>I3-4</i>	378.444098	379.1743	0.009309	374.581065	378.7628	0.056070
<i>I3-5</i>	383.012522	383.0546	0.000507	379.358863	382.6510	0.041484
<i>I3-6</i>	378.655553	378.9743	0.004052	375.057750	378.5549	0.046593

Table C.1.6: Output Temperatures for Detailed and Sub-models 7 and 8 and Corresponding Errors of GaN Model with Five-Port Configuration

Output	Model-7			Model-8		
	T _{full}	T _{sub}	Error	T _{full}	T _{sub}	Error
	(K)	(K)		(K)	(K)	
<i>T-max</i>	400.129321	404.3345	0.041997	396.425717	400.4421	0.041653
<i>I1-1</i>	371.101498	373.8512	0.038673	372.007359	369.9323	0.028817
<i>I1-2</i>	375.268368	380.9912	0.076032	376.161352	377.0456	0.011610
<i>I1-3</i>	371.707607	375.7006	0.055684	372.452728	371.3765	0.014854
<i>I1-4</i>	379.186365	378.5425	0.008131	375.925792	374.3166	0.021194
<i>I1-5</i>	384.784434	386.5575	0.020913	381.498365	382.2701	0.009469
<i>I1-6</i>	379.775579	379.6040	0.002151	376.539730	375.3861	0.015072
<i>I2-1</i>	380.676892	379.4674	0.014992	373.481830	375.0304	0.021074
<i>I2-2</i>	386.895966	388.1947	0.014946	379.772373	383.9076	0.051838
<i>I2-3</i>	381.269490	380.9628	0.003774	374.371938	376.5676	0.029523
<i>I2-4</i>	377.155963	380.1547	0.038866	373.730154	375.7563	0.027481
<i>I2-5</i>	383.546467	386.5827	0.036342	380.075396	382.2962	0.027734
<i>I2-6</i>	378.107177	379.8390	0.022172	374.699509	375.5546	0.011447
<i>I3-1</i>	380.161606	379.2581	0.011271	376.597098	374.7187	0.024523
<i>I3-2</i>	385.894675	386.9254	0.012000	382.283089	382.5741	0.003537
<i>I3-3</i>	380.777429	380.3609	0.005157	377.232704	375.9729	0.016312
<i>I3-4</i>	373.635369	377.4921	0.052376	373.577209	373.0570	0.007070
<i>I3-5</i>	378.406397	381.4083	0.038286	378.093188	377.0543	0.013303
<i>I3-6</i>	374.124718	377.2697	0.042428	373.821361	372.7762	0.014158

C.2 GaAs Based Power Amplifier

Table C.2.1: Output Temperatures for Detailed and Sub-models 3 and 4 and Corresponding Errors of GaAs Model

Output	Model-3			Model-4		
	T _{full} (K)	T _{sub} (K)	Error	T _{full} (K)	T _{sub} (K)	Error
<i>T-max</i>	466.959273	467.4175	0.002745	462.113724	463.0620	0.005849
<i>I1-1</i>	400.933000	398.8891	0.020250	397.900300	395.9656	0.019762
<i>I1-2</i>	465.186000	464.0476	0.006892	462.806500	460.3526	0.015072
<i>I1-3</i>	454.038100	451.5427	0.016200	450.005000	448.0243	0.013204
<i>I2-1</i>	402.905900	401.3975	0.014658	399.456900	398.4309	0.010316
<i>I2-2</i>	469.005700	466.8773	0.012594	464.174500	463.3053	0.005294
<i>I2-3</i>	455.570600	454.2839	0.008271	451.743900	450.7203	0.006746
<i>I3-1</i>	402.657000	401.7431	0.008902	400.432000	398.8297	0.015954
<i>I3-2</i>	468.480400	467.9114	0.003377	466.571200	464.3899	0.013095
<i>I3-3</i>	455.620700	455.0404	0.003729	452.422700	451.4948	0.006088
<i>I4-1</i>	400.628900	398.5822	0.020339	398.183400	395.6680	0.025619
<i>I4-2</i>	463.212400	462.3041	0.005565	460.428400	458.7241	0.010623
<i>I4-3</i>	452.572000	450.9469	0.010651	448.677000	447.5657	0.007475

Table C.2.2: Output Temperatures for Detailed and Sub-models 5 and 6 and Corresponding Errors of GaAs Model

Output	Model-5			Model-6		
	T _{full} (K)	T _{sub} (K)	Error	T _{full} (K)	T _{sub} (K)	Error
<i>T-max</i>	451.281164	454.2994	0.019951	455.506945	457.4616	0.012570
<i>I1-1</i>	390.150000	389.6311	0.005756	392.735500	392.0576	0.007310
<i>I1-2</i>	455.395800	452.4566	0.018914	457.169700	455.4303	0.011067
<i>I1-3</i>	441.449000	440.6346	0.005758	445.662800	443.3817	0.015660
<i>I2-1</i>	392.685400	391.9284	0.008167	395.978000	394.3886	0.016560
<i>I2-2</i>	458.118300	455.4911	0.016615	460.292400	458.3708	0.011988
<i>I2-3</i>	445.479500	443.2676	0.015204	446.630100	446.0029	0.004277
<i>I3-1</i>	392.786800	392.3772	0.004414	395.942000	394.8026	0.011876
<i>I3-2</i>	456.599500	456.5642	0.000225	461.795000	459.4450	0.014525
<i>I3-3</i>	446.606900	443.9252	0.018292	448.747800	446.7052	0.013732
<i>I4-1</i>	389.684800	389.0874	0.006661	392.960600	391.5773	0.014880
<i>I4-2</i>	452.126200	451.2300	0.005891	455.688800	453.9853	0.010942
<i>I4-3</i>	442.191300	440.2070	0.013955	445.340500	442.9578	0.016394

Table C.2.3: Output Temperatures for Detailed and Sub-models 7 and 8 and Corresponding Errors of GaAs Model

Output	Model-7			Model-8		
	T _{full} (K)	T _{sub} (K)	Error	T _{full} (K)	T _{sub} (K)	Error
<i>T-max</i>	464.222617	464.9249	0.004276	467.302146	467.8300	0.003155
<i>I1-1</i>	400.224800	397.2545	0.029636	401.043500	399.1539	0.018701
<i>I1-2</i>	464.322900	461.9563	0.014402	465.478300	464.3668	0.006717
<i>I1-3</i>	450.852300	449.5363	0.008724	453.572300	451.8469	0.011235
<i>I2-1</i>	401.221300	399.7264	0.014769	403.023800	401.6695	0.013146
<i>I2-2</i>	465.458400	464.8165	0.003880	467.299200	467.1675	0.000787
<i>I2-3</i>	454.175800	452.2453	0.012521	454.684900	454.6033	0.000528
<i>I3-1</i>	401.052500	400.0924	0.009501	402.939200	402.0012	0.009112
<i>I3-2</i>	468.760400	465.8801	0.017067	468.241600	468.2030	0.000229
<i>I3-3</i>	455.189500	453.0096	0.014047	456.513500	455.3616	0.007360
<i>I4-1</i>	398.216100	396.9803	0.012582	400.954200	398.9048	0.020300
<i>I4-2</i>	462.539400	460.3057	0.013743	462.988000	462.7095	0.001709
<i>I4-3</i>	449.868800	449.0649	0.005364	451.422300	451.3163	0.000700

Table C.2.4: Output Temperatures for Detailed and Sub-models 9 and 10 and Corresponding Errors of GaAs Model

Output	Model-9			Model-10		
	T _{full} (K)	T _{sub} (K)	Error	T _{full} (K)	T _{sub} (K)	Error
<i>T-max</i>	465.084253	465.8267	0.004497	457.366776	459.2074	0.011696
<i>I1-1</i>	399.980800	397.8279	0.021533	395.990700	393.2655	0.028390
<i>I1-2</i>	464.760300	462.6823	0.012612	457.636300	456.9407	0.004413
<i>I1-3</i>	450.488000	450.2358	0.001676	445.520400	444.8024	0.004934
<i>I2-1</i>	401.694700	400.3316	0.013404	395.823800	395.6746	0.001557
<i>I2-2</i>	466.878300	465.5528	0.007943	460.161500	459.9264	0.001468
<i>I2-3</i>	454.038000	452.9782	0.006880	449.408100	447.4856	0.012867
<i>I3-1</i>	401.155500	400.6947	0.004555	396.669900	396.0972	0.005924
<i>I3-2</i>	468.646500	466.6196	0.012019	463.564200	461.0326	0.015478
<i>I3-3</i>	455.850500	453.7529	0.013459	448.752200	448.2305	0.003507
<i>I4-1</i>	399.785000	397.6024	0.021873	393.453200	392.9408	0.005483
<i>I4-2</i>	462.514700	461.0795	0.008831	458.526200	455.5433	0.018816
<i>I4-3</i>	451.453500	449.7890	0.010990	445.795100	444.4757	0.009050

C.3 Package Model

Table C.3.1: Output Temperatures for Detailed and Sub-models 3 and 4 and Corresponding Errors of Four-Package Model with Right-side BC

Output	Model -3			Model -4		
	T _{full}	T _{sub}	Error	T _{full}	T _{sub}	Error
	(K)	(K)		(K)	(K)	
<i>T-max</i>	348.988662	344.8530	0.084421	349.009553	344.9260	0.083322
<i>P1</i>	331.921227	329.4067	0.078773	331.856623	329.4482	0.075602
<i>P2</i>	334.648289	331.8775	0.079969	334.636274	331.9240	0.078307
<i>P3</i>	334.619682	331.8755	0.079267	334.666009	331.9220	0.079156
<i>P4</i>	331.840866	329.4088	0.076382	331.939772	329.4503	0.077943
<i>P5</i>	334.550005	331.8734	0.077470	334.486828	331.9199	0.074432
<i>P6</i>	340.890717	338.7699	0.051865	340.879809	338.8233	0.050306
<i>P7</i>	340.861495	338.7585	0.051466	340.910327	338.8119	0.051293
<i>P8</i>	334.469492	331.8656	0.075542	334.570353	331.9121	0.076894
<i>P9</i>	334.349572	331.8754	0.072029	334.287852	331.9219	0.069003
<i>P10</i>	340.685547	338.7701	0.047079	340.676126	338.8235	0.045546
<i>P11</i>	340.656272	338.7725	0.046334	340.706648	338.8260	0.046200
<i>P12</i>	334.268906	331.8700	0.070002	334.371350	331.9165	0.071421
<i>P13</i>	331.357038	329.4121	0.062026	331.296592	329.4536	0.058888
<i>P14</i>	334.084109	331.8789	0.064699	334.076225	331.9254	0.063118
<i>P15</i>	334.055377	331.8771	0.063963	334.105960	331.9237	0.063985
<i>P16</i>	331.276272	329.4124	0.059594	331.379627	329.4539	0.061369

Table C.3.2: Output Temperatures for Detailed and Sub-models 3 and 4 and Corresponding Errors of Four-Package Model with Back-side BC

Output	Model -3			Model -4		
	T _{full}	T _{sub}	Error	T _{full}	T _{sub}	Error
	(K)	(K)		(K)	(K)	
<i>T-max</i>	345.645632	344.2785	0.029951	345.745448	344.3766	0.029923
<i>P1</i>	322.235017	320.0867	0.096619	322.311589	320.1627	0.096313
<i>P2</i>	326.040444	323.5012	0.097512	326.127268	323.5846	0.097319
<i>P3</i>	326.035241	323.4982	0.097446	326.134065	323.5817	0.097664
<i>P4</i>	322.220174	320.0896	0.095885	322.329555	320.1654	0.096919
<i>P5</i>	326.115202	323.4945	0.100352	326.191942	323.5780	0.099799
<i>P6</i>	335.001376	333.1749	0.052183	335.089624	333.2696	0.051868
<i>P7</i>	334.996058	333.1592	0.052488	335.096905	333.2546	0.052492
<i>P8</i>	326.100285	323.4842	0.100232	326.210617	323.5682	0.100815

<i>P9</i>	326.109430	323.4973	0.100045	326.185550	323.5806	0.099480
<i>P10</i>	334.995292	333.1755	0.052001	335.083052	333.2703	0.051670
<i>P11</i>	334.989898	333.1786	0.051766	335.090370	333.2731	0.051788
<i>P12</i>	326.094303	323.4892	0.099834	326.204312	323.5727	0.100427
<i>P13</i>	322.218686	320.0941	0.095622	322.293578	320.1699	0.095260
<i>P14</i>	326.023699	323.5027	0.096873	326.109230	323.5857	0.096653
<i>P15</i>	326.018311	323.5003	0.096778	326.116103	323.5837	0.096967
<i>P16</i>	322.203287	320.0944	0.094981	322.311760	320.1700	0.095992

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