Feedback Control of
Organometallic Vapor-Phase Epitaxial Growth of
Aluminum Gallium Arsenide Devices

by

Sean C. Warnick

Submitted to the Department of Electrical Engineering and Computer Science
in partial fulfillment of the requirements for the degree of
Masters of Science in Electrical Engineering
at the
MASSACHUSETTS INSTITUTE OF TECHNOLOGY
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Abstract

This research explores the real-time control of OMVPE growth of AlGaAs thin-films using spectroscopic ellipsometry as a sensor technology. It is shown that control of film thickness and composition is sufficient for repeatable growth, and a process model is developed accordingly. Although descriptive of the growth dynamics, this model is nonlinear, MIMO, and characterized by parametric uncertainty. Controller synthesis is discussed in light of these difficulties, and it is argued that LTI controllers are too conservative for practical applications. A nonlinear synthesis method is then presented based on approximate model-inversion and linear design techniques, and a simple controller is developed promising robust asymptotic tracking despite time-delay, saturation, and the system's sampled-data structure. The performance of this controller is simulated under a variety of conditions, and it is then implemented on an advanced OMVPE reactor. Experimental results verify controller performance and demonstrate feedback's potential for enhancing OMVPE growth.

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## Contents

List of Figures ........................................... 7

List of Tables ............................................ 9

1 Introduction ............................................ 10

1.1 Motivation ............................................. 10

1.1.1 Why Study OMVPE? .................................. 10

1.1.2 Why Consider Feedback Control of OMVPE? .......... 12

1.1.3 Why Consider OMVPE as an Application of Control Theory? 13

1.2 Previous Work ......................................... 13

1.2.1 OMVPE Process Modeling ........................... 14

1.2.2 In-Situ Monitoring ................................. 14

1.2.3 Epitaxial Process Control ........................... 15

1.3 Contributions ......................................... 15

1.4 Organization .......................................... 15

2 Problem Definition ...................................... 16

2.1 Organometallic Vapor-Phase Epitaxy ................... 16

2.1.1 Background Physics ................................ 16

2.1.2 Reactor Performance ................................ 21

2.1.3 Experimental Set-Up ............................... 23

2.2 Spectroscopic Ellipsometry ............................ 25

2.2.1 Sensor Physics ..................................... 26

2.2.2 Extraction of Film Properties ...................... 29

2.2.3 In-Situ Measurements of Open Loop Growth ....... 32
3 Controller Design and Implementation

3.1 Model Linearization

3.1.1 Taylor-Series Expansion

3.1.2 Model Inversion

3.2 Controller Design

3.2.1 Thickness Control

3.2.2 Composition Control

3.3 Simulation Study

3.4 Experimental Results

4 Conclusion

4.1 Summary

4.2 Directions of Future Research

References
List of Figures

2-1 OMVPE reactor configuration .................................................. 18
2-2 Contour map of a AlGaAs quantum-well laser showing excellent uniformity 22
2-3 Spire MOCVD reactor model SPI-MOCVD™ 400SL with a temperature controlled shower-head reactant injector, built-in ellipsometer for in-situ measurements, and load-lock for non-contaminating wafer placement ........... 24
2-4 Spectroscopic ellipsometer experimental set-up .......................... 26
2-5 Reflection of a plane wave by an ambient-film-substrate system .......... 27
2-6 Nominal trajectory for the example system computed for a wavelength of 408.6nm using the database of optical constants for AlGaAs .................. 30
2-7 Database of optical constants for AlGaAs around 720 °C ................. 30
2-8 Noise in Ψ and Δ caused by rotation wobble at 720 °C .................... 33
2-9 Ψ and Δ measured in-situ at 720 °C over 44 wavelengths ................. 33
2-10 Spirals generated by in-situ measurement of AlGaAs/GaAs heterostructure 35
2-11 The objective is to design K so that the closed loop system tracks R ...... 36
3-1 Process nonlinearity f is a static function of the controls ................. 42
3-2 Taylor-series expansion can occur about a nominal trajectory ............ 43
3-3 Linearizing f introduces significant modeling error for most compositions . 44
3-4 Decompose $K_{NL}$ into a linear dynamic system $K$ and static nonlinearity $F$ 46
3-5 Linear $P$ allows $K$ to be chosen using linear design methodologies ........ 46
3-6 Even with a 20% variation in $K_c$, $P_2$ is almost linear .................. 47
3-7 $K_1$ is chosen so the closed-loop system tracks ramp commands .......... 48
3-8 Root locus with a fourth order Pade approximation to a delay of 15 seconds 49
3-9 $K_2$ is chosen so the closed-loop system tracks step commands .......... 50
3-10 Positive Nyquist plot of the integrator system distorted by a 15 second delay 52
3-11 Simulation of open loop performance ........................................ 55
3-12 Simulation of closed loop performance ................................. 55
3-13 Simulated noise on the sensor measurements ....................... 56
3-14 Closed loop control signals ............................................... 56
3-15 Closed loop significantly improves over open loop growth ........ 57
3-16 Simulated growth of a GRINSCH quantum-well laser structure .... 57
3-17 Results of time variations in $K_{gr}$ and $K_c$ ......................... 58
3-18 Verge of instability verified by simulation ............................ 58
3-19 Run M792: Feedback enabled at 500 seconds ....................... 60
3-20 Run M792: Controller tracks composition despite erroneous control setpoints 60
3-21 Run M799: Feedback enabled at 2350 seconds ..................... 61
3-22 Run M799: Controller tracks composition despite saturating controls .... 61
3-23 Run M7106: It becomes increasingly harder to measure the thick film ... 63
3-24 Run M799: Feedback enabled at 1000 seconds ..................... 63
List of Tables

1.1 Overview of epitaxy techniques ........................................ 11
3.1 Model parameter specifications ......................................... 54
Chapter 1

Introduction

1.1 Motivation

This research investigates the degree feedback can improve the performance of organometallic vapor-phase epitaxial (OMVPE) growth of submicron thin-films. Since the growth of different material systems involves fundamentally different chemical processes, a relatively simple but important ternary compound, AlGaAs, is used as the focus of this preliminary research. The immediate goal is to implement feedback control in the real-time growth of AlGaAs, gaining insight into the nature of the control problem and the degree feedback can improve device performance. Fundamentally, then, the motivation for this research revolves around three questions: why study OMVPE, why consider feedback control of OMVPE, and why consider OMVPE as an application of control theory.

1.1.1 Why Study OMVPE?

Epitaxy, the growth of a (single) crystalline substance on a crystalline substrate (wafer), is a critical process for producing components crucial to a variety of industries. These components include lasers, infrared detectors, solar cells, and ultra-high-speed transistors, used in applications such as fiber optic and wireless communication systems, high definition displays, high-density optical data-storage devices, and satellite systems.

Although there are a number of epitaxy techniques, including Liquid-Phase Epitaxy (LPE), Chloride and Hydride Vapor Phase Epitaxy (CIVPE, HVPE), Molecular Beam Epitaxy (MBE), and Organometallic Vapor Phase Epitaxy (also called metalorganic chemical
vapor deposition (MOCVD) or other variations of the same theme), OMVPE has the best potential for sustained profitability. This economic edge is the result of OMVPE's capability for high throughput, high quality growth, complete versatility, and relative low cost.

<table>
<thead>
<tr>
<th>Technique</th>
<th>Strengths</th>
<th>Weaknesses</th>
</tr>
</thead>
<tbody>
<tr>
<td>LPE</td>
<td>Simple</td>
<td>Scale economics</td>
</tr>
<tr>
<td></td>
<td>High purity</td>
<td>Inflexible</td>
</tr>
<tr>
<td></td>
<td>High growth rate</td>
<td>Nonuniformity</td>
</tr>
<tr>
<td>CIVPE</td>
<td>Simple</td>
<td>No Al alloys</td>
</tr>
<tr>
<td></td>
<td>High purity</td>
<td>Sb alloys difficult</td>
</tr>
<tr>
<td></td>
<td>High growth rate</td>
<td>$\geq 20\text{Å}$ interface widths</td>
</tr>
<tr>
<td>MBE</td>
<td>Simple process</td>
<td>As/P alloys difficult</td>
</tr>
<tr>
<td></td>
<td>Uniform</td>
<td>“Oval” defects</td>
</tr>
<tr>
<td></td>
<td>Abrupt interfaces</td>
<td>Expensive (capital)</td>
</tr>
<tr>
<td></td>
<td>Feedback Control</td>
<td>Low throughput</td>
</tr>
<tr>
<td></td>
<td>Repeatable</td>
<td></td>
</tr>
<tr>
<td>OMVPE</td>
<td>High throughput</td>
<td>Expensive reactants</td>
</tr>
<tr>
<td></td>
<td>Most versatile</td>
<td>Most parameters to specify</td>
</tr>
<tr>
<td></td>
<td>Abrupt interfaces</td>
<td>Hazardous precursors</td>
</tr>
<tr>
<td></td>
<td>Simple reactor</td>
<td></td>
</tr>
<tr>
<td></td>
<td>High purity</td>
<td></td>
</tr>
</tbody>
</table>

Table 1.1: Overview of epitaxy techniques

In an economic analysis conducted by EMCORE Corporation, throughput, or the number of successful epitaxial growths per unit time, was identified as the single most important factor affecting profitability of an epitaxial system [15]. The high volume production capability of OMVPE, reportedly as large as 70 two-inch wafers per run [9], thus gives it a clear advantage over single-wafer techniques such as MBE.

Moreover, OMVPE is undoubtedly the most versatile epitaxy method. Not only is it the most widely used method for growing devices containing phosphorous alloys (e.g. InGaAsP) [9], but it has the capability of producing devices that are extremely difficult to grow by other techniques. For example, a superlattice (repeated “sandwich”) structure of GaAsP/InGaAs is unique to OMVPE since it is the only technique capable of growing several different III-V alloy systems in the same physical apparatus, in any sequence, during a single deposition run [21].

For many years the purity, uniformity, and capability of OMVPE for abrupt transitions between layers was noticeably inferior to other epitaxy methods. AlGaAs lasers were among
the most difficult devices to grow, but gradual success demonstrated OMVPE’s ability to produce AlGaAs films with excellent optical properties [21]. Although a primary attraction to MBE and LPE remains the excellent quality of films they generate, OMVPE has now firmly established itself as a comparable technique for growing high quality films of virtually any III-V or II-VI compound [28].

Finally, OMVPE uses a simple reactor system that is relatively inexpensive compared with other techniques. In 1993, for example, a basic multi-wafer OMVPE reactor was listed at $500,000—less than half the cost of a typical MBE system [9]. Also, OMVPE is not hampered with the cost of maintaining the ultrahigh vacuum growth environment used in MBE. These factors, combined with savings from easy maintenance, give OMVPE a clear advantage for a stronger bottom line.

1.1.2 Why Consider Feedback Control of OMVPE?

Despite the advantages and clear potential of OMVPE, the current lack of process repeatability seriously undermines its success. Not only does OMVPE have the most growth parameters to control, but even fixing these parameters can result in different film thicknesses and compositions from run to run. With adequate in-situ sensor technology, however, feedback control represents the best way to achieve true repeatability—the consistent growth of desired structures with first-pass success.

This kind of repeatability is necessary for OMVPE to realize its full economic potential. OMVPE is especially hurt by failed runs because it uses expensive reactants—wasted by the excessive calibration runs needed to get in the ballpark of a desired structure. Moreover, these runs dramatically increase operator hours, driving-up overhead and the effective device cycle-time. Even with stringent calibration procedures, repeatability can be so poor as to ruin batch loads, devastating throughput and profitability.

Feedback control may also be the only way to achieve the precision needed for OMVPE to realize its scientific potential. The development of new complex devices—some only produced by OMVPE—clearly hinges on the ability to grow high quality films to precise specifications. Moreover, OMVPE is already propelling materials research into spinoff technologies of its own, including novel superconducting, ferroelectric, diamond, nitride, ceramic, and even organic film technologies [5]. Controlled growth can only enhance this progress.
1.1.3 Why Consider OMVPE as an Application of Control Theory?

Not only does the progress of materials research using OMVPE reed feedback control, but recent cuts in governmental funding has forced control theorists to seek funding from dual-use technologies. OMVPE is a technology that is critical for the development of a high-tech national infrastructure, and it has clear military applications in supporting atmospheric sensing, night vision, and tactical systems technologies. On the other hand, Japanese investors, who maintain a dominant presence controlling 74.2% of III-V wafer production [20], have anticipated a growing commercial market for compound semiconductor and related devices grown by OMVPE. Mark Fine, business area manager for compound semiconductors at Air Products, reports, “Japanese semiconductor manufacturers have felt they needed the high throughput of MOCVD technology. In addition, they saw compound semiconductor devices as a potential spinoff of silicon technology; MOCVD has a lot of similarities to high throughput silicon processing techniques [9].” This broad applicability secures a reliable funding source for innovative systems research.

The shift from traditional projects to those sponsored by dual-use technologies does not represent an abandonment of central research themes, however. On the contrary, the feedback control of OMVPE addresses two of the most critical issues in control theory—nonlinearity and uncertainty—with a project simple enough for thorough study. Moreover, these issues can not be waved off with mere Taylor-series expansion or overbounding with an unstructured uncertainty disk; effective controller designs must be nonlinear and cope with specific parametric uncertainty in the process model. Other challenges with controlling this process include transport delays, digital/analog hybrid effects, and complex sensor dynamics. Future work may need to explore the infinite-dimensional problem involved with temperature control, the effect of distributed control over all growth parameters, or the extensive identification of control-oriented models of various material-systems’ growth processes. Clearly the problems relevant to controlling OMVPE are central to current trends in control theory and can motivate an assortment of advanced research.

1.2 Previous Work

OMVPE research began in the late 1960's with the work of Manasevit [28], who systematically explored deposition of virtually all of the III-V compounds [21]. A decade later Dupuis
and Dapkus motivated widespread interest in OMVPE by demonstrating the growth of Al-GaAs lasers comparable to standard LPE grown material [21]. Since then, tremendous efforts have been made to understand and control the process (open-loop). Early research in the 1980's focused on hydrodynamic aspects of OMVPE, simulating the flow of source gases and their effect on growth. Results of these studies lead to improved reactor design and the development of useful process models. Simultaneously, significant advances with in-situ monitoring technology lead to the rapid success of feedback control for MBE [3]. Feedback control of OMVPE has recently become a focus of interest, and successful results are beginning to appear in the literature.

1.2.1 OMVPE Process Modeling

Process Modeling for general chemical vapor deposition reactors began to experience limited success in the mid-1980's [11, 12]. Silicon was the focus of these studies, but attempting to numerically solve Navier-Stokes equations always involved the extensive computation necessary for finite-element analysis. More work began to draw on early computational results, and it focused on reactor geometry as a tool for reducing process complexity and enhancing the uniformity of film growth across the wafer surface [26, 31]. Stringfellow [28] organized much of the published material on OMVPE in 1989 and proposed a "consolidated growth model". Although vague and complicated, the value of this "model" is primarily in hypothesizing physical bases for a number of published empirical results.

1.2.2 In-Situ Monitoring

A variety of in-situ monitoring techniques have likewise been developed for OMVPE and the related processes, although vacuum-based growth methods (such as MBE) have successfully used in-situ characterization and even feedback control since the mid-1980's. Accurate in-situ measurements for OMVPE began to be reported extensively around 1990 using optical reflectance methods such as photoreflectance [10], laser reflectance [25], and other variations [16, 19]. Novel characterization methods relating optical properties of thin-films to thickness and composition then began to appear [24, 27], with much of the ellipsometric work reported by Aspnes and co-workers at Bellcore using MBE [1, 2]. This success of spectroscopic ellipsometry for monitoring, and even controlling, growth by MBE has subsequently motivated interest into its use as a tool for the in-situ characterization OMVPE.
1.2.3 Epitaxial Process Control

Considerable success has been reported with feedback control of MBE and CBE, with much of the work in this area published by Aspnes [4, 3, 2]. Reporting the first closed-loop growth for MBE in 1990, and building on that success to grow complicated structures such as AlGaAs parabolic quantum wells [3], Aspnes et al. have paved the way for the ellipsometric control of OMVPE. Wollam and co-workers have subsequently used ellipsometry to control the growth rate of CdTe and the composition of HgCdTe, by OMVPE, in 1993 and 1994 respectively [18, 23]. No closed loop results have been reported for AlGaAs growth by OMVPE.

1.3 Contributions

This research initiates a comprehensive investigation of the feedback control of OMVPE by demonstrating closed-loop growth of AlGaAs using spectroscopic ellipsometry. Specific contributions are:

- A control-oriented process model is developed from Stringfellow's work that describes the growth of III-V ternary systems,

- Mathematical structure of the model is exploited to outline a controller synthesis procedure compatible with classical, $H_\infty$, or $l_1$ design methods,

- A simple controller is developed, simulated, and implemented on an advanced OMVPE reactor, demonstrating composition control of AlGaAs and thickness control of GaAs.

1.4 Organization

This thesis is organized to introduce members of the controls community to OMVPE as a promising application of systems theory. Chapter 2 presents background material necessary to develop a process model and generate a precise statement of the control problem. Chapter 3 discusses controller synthesis relative to the formulated problem, presents a controller design, and reports simulation and experimental results. Chapter 4 summarizes the findings of this research and outlines directions of future work.
Chapter 2

Problem Definition

This chapter presents an overview of OMVPE and spectroscopic ellipsometry, explaining background material necessary to develop a process model. This process model, approximating the growth behavior of many III-V ternary compounds, is then used to formulate a precise statement of the control problem.

2.1 Organometallic Vapor-Phase Epitaxy

The performance of devices grown by OMVPE is affected by a number of parameters including film thicknesses, compositions, wafer uniformity, doping levels, surface morphology, defects, etc. For many devices and material systems, film thicknesses and compositions play the critical role in determining performance (and thus repeatable growth)—provided a reasonable uniformity and structural perfection is achieved. Since this study considers AlGaAs/GaAs devices, structural considerations are not an issue. This section thus discusses the physics underlying OMVPE and describes the relation between controllable parameters to thickness and composition. Data verifying the excellent uniformity achieved by the reactor used in this study is then presented, followed by a description of the OMVPE experimental set-up.

2.1.1 Background Physics

As the name suggests, OMVPE is a process utilizing organometallic source gases to deposit thin crystalline films on a wafer substrate. Other names for the process include Metal-Organic Chemical Vapor Deposition (MOCVD) or various permutations of these letters
(OMCVD and MOVPE). While all of these names refer to the same process, the term OMVPE will be used in this study since it implies that single-crystalline, not polycrystalline or amorphous, epitaxial layers are considered.

Simply put, OMVPE is a process for depositing a film of a specified thickness (e.g. 100 Angstroms) and composition (e.g. percent aluminum, $100 \times x$, in $Al_xGa_{1-x}As$), with possibly other properties of interest (doping level, etc.), on a particular substrate. Device fabrication requires the growth of multiple layers sandwiched in a particular structure. Since the actual quantity of interest is device performance, precise and repeatable growth over the entire wafer surface is critical.

Previous research has focused on modeling the fluid dynamics of various reactor geometries in an attempt to maximize uniformity of film properties over the entire wafer surface. This study assumes that the reactor geometry considered does generate uniform films, and it thus focuses on the feedback control of film properties (thickness and composition) themselves. This assumption greatly simplifies the process model and is validated by the experimental data presented in the Reactor Performance section of this chapter.

Figure 2-1 illustrates the main components of a typical OMVPE reactor. The basic idea is that source gases are passed through metal-organic bubblers to pick up specified amounts of group III precursor molecules. These gases are then mixed with the group V gas and possibly a dilution gas in a central manifold before entering the reaction chamber. Although there are many reactor geometries in use, this study considers the use of a vertical warm-wall design that forces the input gas through a temperature controlled “shower-head” screen to generate uniform flow. The gas then passes over the hot wafer substrate mounted on a high speed rotating susceptor where deposition occurs, and finally it is expelled through the exhaust system.

The actual deposition process, however, is actually much more complex. OMVPE is especially complicated because it involves an interplay between thermodynamics, chemical kinetics, and fluid dynamics. A general understanding of each of these aspects provides a foundation for developing a process model and defining an operating regime where it is valid.

Thermodynamics of the process can be used to describe the driving force for epitaxy, and to give an indication of the composition of multi-component solids grown by OMVPE. Thermodynamics is central to OMVPE because, essentially, the growth process is the result
of intentionally creating a non-equilibrium environment at the substrate surface and relying on thermodynamics to drive the system to metastable equilibrium. This driving force, which can be written in terms of the chemical potentials of each phase (solid and vapor), is fundamentally limited by the laws of thermodynamics and the total size of the system, although under normal operating conditions other factors, such as reactant mass-transport, effectively limit the reaction rate. When growth is mass-transport limited, the partial pressures of group III reactants at the growth interface approach zero, thus indicating that all precursor molecules that reach the surface are incorporated into the crystalline film. For ternary alloys of the form $A_xB_{1-x}C$, this implies that equilibrated epilayer composition is given by:

$$X_x = \frac{J_A}{J_A + J_B}$$  \hspace{1cm} (2.1)

where $J_A$ and $J_B$ are the reactant fluxes at the growth interface of species A and B.

While thermodynamics defines the driving force behind the growth process, chemical kinetics controls the rates by which these processes occur. In general, a thorough understanding of the specified chemical reaction and its associated rate provides information
about the time required to attain equilibrium, the actual steps involved in the pursuit of the lowest energy state, and the rates of the various processes occurring during the transition from input gas to crystalline film. As mentioned, although thermodynamics determines the maximum growth rate, usually surface kinetics and mass-transport are not fast enough to allow equilibrium to be established at all times. Thus, two "operating regimes" can be defined, namely the "kinetic-limited" regime and the "mass-transport limited" regime, depending on which process is effectively limiting epitaxial growth. These operating regimes are determined by reactor pressure, \( Pr \), and substrate temperature, \( Ts \). Normal operating pressures, close to 0.2 atmospheres, and temperatures in the range 550 – 750 °C define the mass-transport limited regime; growth at lower temperatures is kinetically-limited.

In the mass-transport limited regime, growth rate and composition are effectively limited by the amount of group III source molecules that reach the wafer surface. Under these conditions, fluid dynamics is clearly an important factor for precision growth. The complete hydrodynamic analysis involves simultaneously solving a system of partial differential equations for conservation of mass, momentum (Navier-Stokes equation), and energy (first law of thermodynamics) in three dimensions using appropriate boundary conditions (which are reactor-specific, depending on the particular geometry considered). Clearly the complexity of a model can grow unreasonably—especially when natural convection resulting from the temperature gradient between the hot substrate and warm walls is considered. Recent developments in reactor geometry, however, have resulted in designs that attempt to minimize this complexity. The vertical warm-wall "shower-head" configuration is one such design. Using a grid-like structure at the inlet, this design attempts to create uniform laminar flow across the entire wafer surface. Under these conditions, the well-known boundary-layer model is a useful approximation to the system hydrodynamics. The idea is to assume that a stagnant layer resides at the growth interface, thus allowing mass-transport only by diffusion. Using this approximation, the following assumptions make the development of a growth model tractable:

1. No parasitic reactions, i.e. all group III source molecules leaving the bubblers reach the growth interface,

2. Ideal gas behavior, i.e. reactants are sufficiently diluted in the vapor phase to justify the use of the ideal gas law,
3. Mass-transport limited and uniform growth, i.e. all group III source molecules at the growth interface are incorporated uniformly into the crystalline film,

4. Stoichiometric growth, i.e. no group V reactant is incorporated into the solid phase without the corresponding minority component,

5. No undesired impurities (e.g. oxygen, etc.) are introduced in the system.

Using these assumptions, the growth rate is simply proportional to the input molar flow rates of the minority components, \( f_{A,B} \), as follows:

\[
G_R = K_{gr} (f_A + f_B) \quad (2.2)
\]

where \( K_{gr} \) is a constant related to the mass-transport of the specific reactor and the diffusion coefficients of species A and B. Likewise, using the boundary layer approximation, the group III flux for species A and B are given by:

\[
J_A = \frac{D_A (p_A^* - p_A^i)}{RT \delta_0} \quad (2.3)
\]

\[
J_B = \frac{D_B (p_B^* - p_B^i)}{RT \delta_0} \quad (2.4)
\]

where \( D_{A,B} \) are the diffusion coefficients, \( p_A^{*}, p_B^{*} \) are the respective input partial pressures of the group III sources, \( p_A^i, p_B^i \) are the group III partial pressures at the interface, \( R \) is the ideal gas constant, \( T \) is the substrate temperature, and \( \delta_0 \) the boundary-layer thickness. Noting that \( p_A^i = p_B^i \approx 0 \) and that \( p_{A,B}^{*} \) is proportional to \( f_A \) and \( f_B \), substituting (2.3) and (2.4) into equation (2.1) then gives:

\[
X_s = \frac{K_c f_A}{f_B + K_c f_A} \quad (2.5)
\]

with \( K_c \) the distribution coefficient (approximately unity), related to the ratio \( D_A/D_B \).

The purpose of the bubbler, then, in the context of this study is to generate a specified mass flow of (group III) reactant. Assuming equilibrium conditions in the bubbler, the partial pressure of the metal-organic (MO) species inside bubbler \( i \) is given by:

\[
\log p_i = b_i - \frac{a_i}{T_i} \quad (2.6)
\]

where \( a_i \) and \( b_i \) are constants related to the specific MO considered, \( T_i \) is the internal
temperature of bubbler $i$ in degrees Kelvin, and $p_i$ is the reactant partial pressure in mmHg. The mole fraction of species $i$ is then given by:

$$X_i = \frac{p_i}{P_{oi}}$$  \hspace{1cm} (2.7)

where $P_{oi}$ is the total pressure in bubbler $i$ measured in units consistent with $p_i$. The reactant flow out of the bubbler, $f_i$, can then be computed in terms of the bubbler’s input, or source, flow, $f_{si}$, as:

$$f_i = \frac{X_i}{1 - X_i} f_{si}$$  \hspace{1cm} (2.8)

This quantity reveals how much (group III) reactant leaves the bubbler. Although arbitrary variations in bubbler source flows can force non-equilibrium conditions—and consequently affect the vapor-phase concentration of reactant leaving the bubbler—TMGa and TMAI are very stable precursors.

Assigning Bubbler 1 to species A (Aluminum), and Bubbler 2 to species B (Gallium), then yields the following model for ternary (AlGaAs) growth in the mass-transport limited regime:

$$T_H = G_R = K_{gr} \begin{bmatrix} \frac{X_1}{1 - X_1} & \frac{X_2}{1 - X_2} \\ f_{s1} & f_{s2} \end{bmatrix}$$  \hspace{1cm} (2.9)

$$X_s = \frac{K_c \frac{X_1}{1 - X_1} f_{s1}}{\frac{X_2}{1 - X_2} f_{s2} + K_c \frac{X_1}{1 - X_1} f_{s1}}$$  \hspace{1cm} (2.10)

where $T_H$ is epilayer thickness. Since reactor temperature and pressure can easily be regulated to maintain growth in the mass-transport limited regime, source flows are clearly adequate as control points to affect thickness and composition. These properties, in turn, are sufficient to maintain repeatability and significantly improve the performance of most devices—provided nominal growth is relatively uniform.

### 2.1.2 Reactor Performance

As mentioned earlier, thickness and composition control is sufficient for repeatable device growth only if the specific reactor used consistently delivers uniform growth over the wafer surface. The advanced reactor design used in this experiment is the result of considerable research and does, in fact, achieve excellent uniformity.
Figure 2-2: Contour map of a AlGaAs quantum-well laser showing excellent uniformity
This uniformity is achieved by minimizing convection in the reaction chamber and maintaining steady, uniform source flow. Convection, caused by the heating of the source gas as it nears the substrate and its subsequent inclination to rise, is reduced in two ways. First, by minimizing the distance between the shower-head gas injector— at the top of the chamber—and the susceptor the chamber maintains a relatively large capacity (up to three 2” substrates or one 4” substrate) while minimizing the active volume. Second, the high speed susceptor rotation coupled with a lower reactor pressure (0.2 atm as opposed to 1 atm) has been shown in extensive studies by Sandia National Laboratory to generate laminar growth by eliminating turbulence [7, 22, 8, 29]. Uniform flow is maintained by the use of a mesh-like grating, or “shower-head”, at the gas intake. Such a design has achieved record uniformity for the growth of AlGaAs, and maintains excellent uniformity even when modified to include optical ports.

Figure 2-2 shows how this uniformity is mapped on a quantum well laser structure analyzed by photo luminescence. The contours show variation in the peak photo luminescence wavelength, which, for this structure, is a sensitive function of quantum-well thickness and composition. This data indicates that the lasing wavelength (the measure of device performance for this structure) is almost constant over the entire surface.

2.1.3 Experimental Set-Up

The OMVPE system used in this study consists of three major components: the reactor, ellipsometry computer, and control computer. Smooth interaction between these devices is essential before real-time control of the growth process can occur.

As described earlier, the reactor consists of a gas handling system (source gas cannisters, metalorganic bubblers, a dilution manifold, etc.), a reaction chamber, and an exhaust system (Figure 2-1). The reactor used in this study is an advanced Spire MOCVD reactor, model SPI-MOCVD\textsuperscript{TM} 400SL (Figure 2-3). Standard mass-flow controllers are used for mass transport in the gas lines, and a custom-designed resistive heater, controlled with a Eurotherm SCR controller, is used to heat the substrate. Reactor pressure is maintained by a MKS pressure controller and a roughing vacuum pump. This reactor is also equipped with EPISON concentration sensors at the output of each bubbler to monitor the amount of group III reactant in the gas stream. Additionally, the reactor is equipped with a Westinghouse Programmable Logic Controller (PLC) and Digital-to-Analog Converter to process
Figure 2-3: Spire MOCVD reactor model SPI-MOCVD™ 400SL with a temperature controlled shower-head reactant injector, built-in ellipsometer for in-situ measurements, and load-lock for non-contaminating wafer placement
commands sent from the control computer. These devices convert control commands to the appropriate voltages used by the respective actuators. A standard RS-232 connection is used to interface the control computer and PLC.

The ellipsometer makes in-situ measurements of the ellipsometric variables Psi, Ψ, and Delta, Δ, (discussed in section 2.2) through special optical ports on the reaction chamber, and sends these measurements to a Gateway 2000 50MHz 486 computer for processing. This computer runs a Microsoft Windows™ based processing routine provided by J.A. Woolam Inc. to operate the ellipsometer and perform the necessary regression needed to convert real-time Ψ and Δ data into a (approximate) thickness or composition measurement. Once a measurement has been made, the computer downloads this value to a protocol switch where it can be read by the control computer.

Another Gateway 2000 50MHz 486 serves as the control computer. This computer runs an application developed at Spire Corporation that facilitates the high level construction and implementation of a run log, or table of commands specifying the OMVPE reactor parameters (e.g. source flows, reactor temperature and pressure, etc.) at each stage of growth. For example, a typical run log would begin with Warm-Up (log line 1: heats substrate to growth temperature) and Arsine Stabilization (log line 2: flushes arsine line and establishes steady flow). The next few lines in the run log would specify the growth parameters for a particular device; each log line corresponding to a film or layer of the device. Finally, the last line of the run log is for Cool-Down, in preparation for the removal of the device wafer.

A feedback control algorithm can be implemented as a subroutine of this larger, operating code, and it specifically needs to interface with the protocol switch to receive periodic measurements from the ellipsometry computer. Adjustments are then made to the “setpoints” of the appropriate control parameters (source flows of the TMAI and TMGA bubblers specified in the Run Log) before they are downloaded to the reactor PLC.

### 2.2 Spectroscopic Ellipsometry

Ellipsometry is a method of measuring the state of polarization of a polarized vector wave [6]. In the context of this study, optical ellipsometry of polarized light waves is used as a nonintrusive measurement technique to extract information about the growth of a particular
epitaxial film. In general, the semiconductor device grown by OMOVPE consists of several thin-films sandwiched on an optically "thick" substrate. This sandwich structure acts as an optical system that interacts with incident polarized light to change its state of polarization. Although optical systems in general can modify the state of polarization of an optical probe by either reflection, refraction, transmission, or scattering, this study is concerned with *reflection* ellipsometry, a well-established tool for the study of surfaces and thin films (Figure 2-4). Moreover, the ellipsometer considered uses a broad-band optical probe that measures over a range of wavelengths (400nm - 800nm), hence the name *spectroscopic* ellipsometry.

This section explains the physics underlying ellipsometry, focusing on how a ambient-film-substrate system affects the complex intensity (amplitude and phase) of incident light. The process of extracting information about film properties, such as thickness or composition, from these measured variables is then discussed. Finally, in-situ data taken on the reactor system used in this study is presented.

![Diagram](image)

**Figure 2-4: Spectroscopic ellipsometer experimental set-up**

### 2.2.1 Sensor Physics

The physics underlying ellipsometry are easy to understand when considering the simple ambient-film-substrate system shown in Figure 2-4. That is, consider the case where light is reflected from a substrate covered by a single film. For simplicity it will be assumed that the incident light is monochromatic with (free-space) wavelength \( \lambda \), and that the film has parallel-plane boundaries with thickness \( d \). Moreover, the film (medium 1) is assumed to be sandwiched between semi-infinite ambient (medium 0) and substrate (medium 2) media. All three layers are homogeneous and isotropic, with complex indices of refraction \( N_0, N_1, \)
and $N_2$ respectively.

![Diagram of reflection of a plane wave by an ambient-film-substrate system](image)

**Figure 2-5: Reflection of a plane wave by an ambient-film-substrate system**

When a plane wave is incident in medium 0 and at angle $\phi_0$, a resultant reflected wave is observed in the same medium. The objective of this tutorial is to relate the complex amplitude of the reflected wave to that of the incident wave, when the latter is linearly polarized with components parallel (p) and perpendicular (s) to the plane of incidence (the plane normal to the film surface that contains the incident and reflected beams). The following discussion draws heavily from Azzam’s work [6], which explains the analysis originally due to Drude.

Figure 2-5 illustrates the action of the ambient-film-substrate optical system on an incident beam. Note that at each interface, part of the wave is reflected while the remainder is refracted into one of the semi-infinite media. Basic electromagnetic theory yields Fresnel's reflection and transmission coefficients at the 0-1 and 1-2 interfaces to be:

$$r_{01p} = \frac{N_1 \cos \phi_0 - N_0 \cos \phi_1}{N_1 \cos \phi_0 + N_0 \cos \phi_1}$$  \hspace{1cm} (2.11)

$$r_{12p} = \frac{N_2 \cos \phi_1 - N_1 \cos \phi_2}{N_2 \cos \phi_1 + N_1 \cos \phi_2}$$  \hspace{1cm} (2.12)

$$r_{01s} = \frac{N_0 \cos \phi_0 - N_1 \cos \phi_1}{N_0 \cos \phi_0 + N_1 \cos \phi_1}$$  \hspace{1cm} (2.13)

$$r_{12s} = \frac{N_1 \cos \phi_1 - N_2 \cos \phi_2}{N_1 \cos \phi_1 + N_2 \cos \phi_2}$$  \hspace{1cm} (2.14)

$$t_{01p} = \frac{2N_0 \cos \phi_0}{N_1 \cos \phi_0 + N_0 \cos \phi_1}$$  \hspace{1cm} (2.15)
\[
t_{12p} = \frac{2N_1 \cos \phi_1}{N_2 \cos \phi_1 + N_1 \cos \phi_2}
\]
(2.16)

\[
t_{01s} = \frac{2N_0 \cos \phi_0}{N_0 \cos \phi_0 + N_1 \cos \phi_1}
\]
(2.17)

\[
t_{12s} = \frac{2N_1 \cos \phi_1}{N_1 \cos \phi_1 + N_2 \cos \phi_2}
\]
(2.18)

where \(\phi_1\) and \(\phi_2\) are the (complex) angles of refraction in the film and substrate. Complex angles \(\phi_0\), \(\phi_1\), and \(\phi_2\) are considered when any of the media is absorbing, and they are related by Snell’s law:

\[
N_0 \sin \phi_0 = N_1 \sin \phi_1 = N_2 \sin \phi_2
\]
(2.19)

Note that each time the wave trapped inside the film is reflected back, it experiences a change of phase. This phase-change is a function of wavelength \(\lambda\), film thickness \(d\), the film’s complex index of refraction \(N_1\), and the film’s complex angle of refraction \(\phi_1\), referred to as the film phase thickness, this change of phase is given by:

\[
\beta = 2\pi \left( \frac{d_1}{\lambda} \right) N_1 \cos \phi_1
\]
(2.20)

The total reflected wave in medium 0 for each polarization is given by the sum of the partial waves (dropping polarization subscripts):

\[
R = r_{01} + t_{01} t_{10} r_{12} e^{-j2\beta} + t_{01} t_{10} r_{12}^2 e^{-j4\beta} + t_{01} t_{10} r_{12}^3 e^{-j6\beta} \ldots
\]
(2.21)

which is an infinite geometric series with summation:

\[
R = r_{01} + \frac{t_{01} t_{10} r_{12} e^{-j2\beta}}{1 - r_{10} r_{12} e^{-j2\beta}}
\]
(2.22)

It is easily verified that \(t_{01} t_{10} = 1 - r_{01}^2\). The total complex-amplitude reflection coefficients, relating the amplitude of an incident wave to that of the reflected wave, then become:

\[
R_p = \frac{r_{01p} + r_{12p} e^{-j2\beta}}{1 + r_{01p} r_{12p} e^{-j2\beta}}
\]
(2.23)

\[
R_s = \frac{r_{01s} + r_{12s} e^{-j2\beta}}{1 + r_{01s} r_{12s} e^{-j2\beta}}
\]
(2.24)

Similar reasoning can be used to generate expressions for the complex-amplitude reflection
coefficients for a multi-film structure. The ambient-film-substrate case is of central importance, however, because multi-film structures can be thought of as a simple ambient-film-substrate system where the “substrate” considered is a composite of the actual substrate and all underlying films.

Figure 2-4 shows the physical components of an ellipsometer that contribute to its operation. The source provides a beam of white light of appropriate diameter, bandwidth and collimation. The polarizer linearly polarizes this beam so that components in the p and s directions are non-zero, and the quarter wave plate shifts the phase of the p component of the incident beam, circularly polarizing the light. Since \( R_p \) and \( R_s \) operate differently on the incident light, the reflected beam becomes elliptically polarized. The analyzer, as a rotating polarizer, and the detector, as a photodetector sensitive over the desired bandwidth, then measure two parameters \( \Psi(\lambda) \) and \( \Delta(\lambda) \) related to the nature of this reflected ellipse. The relationship between \( \Psi, \Delta \) and \( R_p, R_s \) at each wavelength \( \lambda \) is given by:

\[
\tan \Psi e^{j\Delta} = \frac{R_p}{R_s} = \frac{r_{01p} + r_{12p}e^{-j2\beta}}{1 + r_{01p}r_{12p}e^{-j2\beta}} \frac{1 + r_{01s}r_{12s}e^{-j2\beta}}{r_{01s} + r_{12s}e^{-j2\beta}}
\]  
(2.25)

Note that since \( N_0, N_1, \) and \( N_2 \) are in general complex, \( \rho \equiv \tan \Psi e^{j\Delta} \) is a function of nine parameters.

2.2.2 Extraction of Film Properties

Although the ellipsometric variables \( \Psi \) and \( \Delta \) are extremely sensitive to changes in thickness and composition, the hardest part about making a real-time measurement is undoubtedly extracting estimates of the film properties from this measured data. This extraction is difficult because at least three of the nine real parameters specifying \( \rho \equiv R_p/R_s \) are unknown, while only two quantities are measured. The unknown variables are the optical constants of the film, \( n \) and \( k \) (where \( N_1 = n - ik \)), and its thickness. Two approaches taken to this extraction problem are a model-based, and a virtual-interface approach.

The model-based approach is relatively simple and conceptually appealing. The idea is to assume a model of the current structure, e.g. a GaAs substrate covered by three 7000 Angstrom layers of AlGaAs, with respective compositions of 30%, 60%, and 30%; assume the current layer is 60% AlGaAs at a growth rate approximately 12 Angstroms/sec. From this model, a database of optical constants is used to estimate the effective optical constants
Figure 2-6: Nominal trajectory for the example system computed for a wavelength of 408.6nm using the database of optical constants for AlGaAs

Figure 2-7: Database of optical constants for AlGaAs around 720 °C
of the existing structure at each wavelength. These effective values are then incorporated into equations (2.11), (2.12), (2.13), (2.14), and (2.25) to compute nominal values, or a nominal trajectory, of $\Psi$ and $\Delta$ (figure 2-6). The error between measured and nominal values is then used to drive a standard gradient-descent algorithm to update parameters of the growing film and minimize the resulting error. Problems with this approach include the fact that modeling error is propagated, and the database of optical constants can be a significant source of error. Figure 2-7 shows the database of optical constants, $n$ and $k$ for AlGaAs at 720 °C.

Another approach to the problem is the virtual-interface approach, which assumes a known growth rate in exchange for a more robust estimation of composition. The idea is to lump the effect of the entire device substructure (the “virtual interface”) on the system’s current optical properties into a single parameter. This parameter and the current composition thus become the only unknown variables in the system, allowing composition to be estimated independently from the measurement of $\Psi$ and $\Delta$. This approach also relies heavily on a database of optical constants of the desired material.

Either approach builds on an approximate understanding of the optical interaction of the material system with incident light. Assumptions needed to support the development presented here are given as follows:

1. Interaction between incident light and the optical system is
   - Linear
   - Frequency-conserving

2. Each component of the optical system under investigation is
   - Non-depolarizing
   - Optically isotropic
   - Homogeneous
   - Bounded with parallel-plane boundaries
   - Non-amplifying

3. Lateral dimension of the sandwich structure must be many times each individual film’s thickness
4. Source bandwidth, beam diameter, degree of collimation, and film thickness of each film in the structure must meet certain technical conditions such that reflected/transmitted waves combine coherently.

These conditions are readily met in most practical applications of ellipsometry, and by the OMVPE growth of AlGaAs in particular.

2.2.3 In-Situ Measurements of Open Loop Growth

Despite the ambiguity in deriving film properties from $\Psi$ and $\Delta$ data, good results have been achieved in the actual real-time measurement of film properties. These results have occurred despite practical difficulties, and they include the real-time characterization of AlGaAs composition, using the virtual-interface algorithm, as well as in-situ thickness measurements of GaAs from a model-based regression.

One of the most challenging practical problems involved with the in-situ measurement is the noise introduced by susceptor rotation wobble (Figure 2-8). This wobble is caused by a slight deformation of the susceptor as it is heated to growth temperature, and it causes the reflected light to wander away from the detector. Since data reported when the light is not focused on the detector is erroneous, it is essential to keep at least part of the beam diameter on the detector at all times. This is accomplished by adjusting the sensor once the susceptor is hot (mid-run) to precisely align the source and detector.

Typical $\Psi$ and $\Delta$ measurements for all 44 wavelengths used by the ellipsometer are shown in Figure 2-9. These measurements were taken in-situ, at typical growth temperature (720 °C), and under normal growth conditions (susceptor rotation at 400 rpm). The device being grown is the example from the previous section, an AlGaAs heterostructure repeating layers with a composition of 60% aluminum and 30% aluminum on a GaAs substrate. Note that longer wavelengths result in prolonged oscillation of both $\Psi$ and $\Delta$. These oscillations indicate that that particular wavelength completely penetrates the growing film and interacts with the underlayer.

While the frequency of these oscillations reveal the growth rate of the film, the steady state value of $\Psi$ or $\Delta$ indicate its composition—hence the difficulty in accurately determining thickness and composition simultaneously (especially at interfaces). Clearly, then, shorter wavelengths, which do not penetrate as far into the film (for AlGaAs), give better data for the composition deposited at the film surface, but quickly “die” to their steady state, or
Figure 2-8: Noise in $\Psi$ and $\Delta$ caused by rotation wobble at 720 °C

Figure 2-9: $\Psi$ and $\Delta$ measured in-situ at 720 °C over 44 wavelengths
bulk values.

Another common way of viewing this data is to plot \( \Delta \) versus \( \Psi \) at each wavelength (Figure 2-10). This technique, used in the "virtual interface" approach of extracting film properties, reveals spiraling trajectories around the bulk value of \((\Psi, \Delta)\) for each respective composition. These characteristic spirals are theoretically exponential in nature, and the range of bulk values from 0\% (GaAs) to 100\% (AlAs) lie on a unique continuum for each wavelength.

2.3 Process Model

Combining features of the input-output behavior of the (idealized) ellipsometer with the OMVPE growth model yields a comprehensive process model \( G \) that facilitates controller design (Figure 2-11). This model has five distinct components: a digital-to-analog hold, time delay, saturation, growth model, and analog-to-digital sampler.

The hold operator \( H_T \) represents the effect of the digital-to-analog conversion in the Westinghouse Programmable Logic Controller (PLC), used to implement the digital commands from the control PC. This operator, mapping a signal \( u(n) \) to \( u(t) \), is defined as:

\[
    u(t) = u(n) \quad nT \leq t \leq (n + 1)T
\]  

(2.26)

where \( T \) is a fixed interval.

The delay operator \( D_r \) models the combined effect of transport delay in the system and the computation time needed for ellipsometric signal processing. Transport delay is a consequence of the source flow needing some time to pass through the bubblers, internal piping, and the dilution manifold. The computation time is due to data averaging and the ellipsometer's fitting algorithm. Together, these effects can be modeled as a pure time delay, mapping a signal \( u(t) \) to \( u_r(t) \), and defined as:

\[
    u_r(t) = u(t - \tau)
\]  

(2.27)

Note that the assumption is made that there exists integer \( m \) such that \( \tau = mT \), thereby allowing the hold and delay operators to commute.

Saturation effects result from hard limits on the achievable flow rates using the exist-
Figure 2-10: Spirals generated by in-situ measurement of AlGaAs/GaAs heterostructure
Figure 2.11: The objective is to design $K$ so that the closed loop system tracks $R$ ing mass flow controllers and piping system. These effects are modeled as an operator $S$ mapping a signal $u_r(t)$ to $u_{sat}(t)$. Note that saturations occur elementwise in a multi-input multi-output system, and thus $S$ is defined for the $i^{th}$ channel as:

$$
u_{sat}^i(t) = \begin{cases} 
  u_{max}^i & u_r^i(t) > u_{max}^i \\
  u_r^i(t) & u_{min}^i \leq u_r^i(t) \leq u_{max}^i \\
  u_{min}^i & u_r^i(t) < u_{min}^i 
\end{cases} \quad (2.28)$$

The growth model developed for mass transport limited growth is used to describe the primary dynamics; the resulting model is uncertain and nonlinear. Define as an operator $P_{NL}$ mapping $u_{r,sat}(t)$ to $z(t)$ as:

$$\dot{x}(t) = K_{gr} \begin{bmatrix} B1 & B2 \end{bmatrix} \begin{bmatrix} u_1(t) \\
  u_2(t) \end{bmatrix} \quad (2.29)$$

$$\begin{bmatrix} y_1(t) \\
  y_2(t) \end{bmatrix} = \begin{bmatrix} 1 \\
  0 \end{bmatrix} x(t) + \begin{bmatrix} 0 \\
  \frac{K_c B_1 u_1(t)}{K_c B_1 u_1(t) + K_c B_1 u_1(t)} \end{bmatrix} \quad (2.30)$$

where $B_1 \equiv X_1/1 - X_1$, $B_2 \equiv X_2/1 - X_2$, and $K_{gr}$ and $K_c$ are constant but uncertain parameters in $\mathbb{R}$ on the closed intervals:

$$K_{gr} \in [K_{gr-lo}, K_{gr-hi}]$$

$$K_c \in [K_{c-lo}, K_{c-hi}]$$

36
Then let $P$ be the set of processes given by all possible values of $K_{gr}$ and $K_c$. Note that the assumption that these parameters are constant is arbitrary but reasonable in the absence of in-situ data suggesting otherwise.

Finally, the effects of using an ellipsometer as the measurement device are taken into account. Although an understanding of the difficulty associated with fitting measurable quantities to generate thickness and composition data may discourage the assumption that the ellipsometer delivers actual measurements, it does provide a good starting point for this preliminary research. It is hoped, then, that data from this study will be instrumental in identifying unmodeled sensor dynamics and noise. The primary effect of the sensor, then, is to sample the output at regular intervals. Modeled as a sampling operator $S_T$ mapping $z(t)$ to $y(n)$, and recalling the interval time $T$ used to define $H_T$, this behavior is described as:

$$y(n) = z(nT) \quad n = 0, 1, 2, \ldots \quad (2.31)$$

Although a number of simplifying assumptions were made to arrive at this model, it does account for the primary effects related to OMVPE growth and ellipsometric characterization of AlGaAs. This comprehensive model $G$, and the set of process $G$ generated by all $P_{NL} \in P$, can then be used to specify the exact problem statement once the following parameters are specified: $T$, $\tau$, $B_1$, $B_2$, $K_{gr-hi}$, $K_{gr-lo}$, $K_{c-hi}$, $K_{c-lo}$, $u_{\text{max}}$, $u_{\text{min}}$, $u_{\text{max}}^2$, and $u_{\text{min}}^2$. The uncertain set of process $G$ is then given by:

$$\dot{x}(t) = K_{gr}[B_1 \quad B_2] \begin{bmatrix} u_{\text{sat}}(t-\tau) \\ u_{\text{sat}}^2(t-\tau) \end{bmatrix}$$

$$z_1(t) = \begin{bmatrix} 1 \\ 0 \end{bmatrix} x(t) + \begin{bmatrix} 0 \\ \frac{K_c B_1 u_{\text{sat}}(t-\tau)}{B_2 u_{\text{sat}}^2(t-\tau) + K_c B_1 u_{\text{sat}}(t-\tau)} \end{bmatrix} \quad (2.33)$$

$$z_2(t) = \begin{bmatrix} 1 \\ 0 \end{bmatrix} x(nT) + \begin{bmatrix} 0 \\ \frac{K_c B_1 u_{\text{sat}}((nT-\tau)}{B_2 u_{\text{sat}}^2(nT-\tau) + K_c B_1 u_{\text{sat}}((nT-\tau)} \end{bmatrix} \quad (2.34)$$

for $t \geq 0$, $n = 0, 1, 2, \ldots$, and:

$$K_{gr} \in [K_{gr-lo} \quad K_{gr-hi}]$$

$$K_c \in [K_{c-lo} \quad K_{c-hi}]$$

37
\[ u_{1\text{sat}}(t) \in \begin{bmatrix} u_{\text{min}}^1 & u_{\text{max}}^1 \end{bmatrix} \]
\[ u_{2\text{sat}}(t) \in \begin{bmatrix} u_{\text{min}}^2 & u_{\text{max}}^2 \end{bmatrix} \]

### 2.4 Problem Statement

There are two primary issues associated with control design in general, stability and performance. When uncertainty is an issue, the notions of robust stability and robust performance are introduced. Robust stability is achieved when a controller maintains internal closed loop stability for all processes in the class defined by the uncertainty model. Robust performance is achieved when a certain performance criterion is met for all processes in the specified class.

There are many performance criteria applicable to the OMVPE control problem. The general objective is that thickness and composition should approach desired values, so one could consider minimizing a particular norm on the error generated between the desired and actual values. For a linear problem, this type of performance criterion would lead to an \( H_{\infty} \) or \( l_1 \) design (depending on the norm used) [13]. Usual synthesis procedures for such methodologies would involve the overbounding of parametric uncertainty, like that in the OMVPE problem, by an unstructured uncertainty "disk" [14]. This overbounding would be prohibitively conservative, however, and is not considered a useful approach at this point. Moreover, with no in-situ data available, it is difficult to know which norm is a more useful performance measure.

Another performance criterion is the notion of asymptotic convergence, that is, that the actual thickness and composition should asymptotically approach the desired values. This notion is more fundamental in the sense that it is compatible with other specifications, such as a limit on percent overshoot or settling time, or even norm constraints like those discussed above, and it is generally easier to achieve since it does not involve solving an optimization problem.

The objective of this research, then, is to design a controller \( K \) that achieves robust performance, in the sense that it maintains stability and asymptotic tracking of a class of reference commands and for all processes in \( \mathcal{G} \). Defining this class of reference commands leads to a precise statement of the objective.

**Definition 2.4.1** A reference command \( R \) is said to be admissible if \( R(t) \in \mathbb{R}^2 \) and its
components are given by:

\[
R_1(t) = \begin{cases} 
0 & 0 < t < t_o \\
G_R(t - t_o) & t \geq t_o 
\end{cases}
\]

\[
R_2(t) = \begin{cases} 
0 & 0 < t < t_o \\
R_2 & t \geq t_o 
\end{cases}
\]

with \( R_2 \in [0, 1] \) and \( G_R \in (0, G_{R\text{max}}] \) where \( G_{R\text{max}} = K_{g-r} - h_i(B_1u_{\text{max}}^4 + B_2u_{\text{max}}^2) \).

Research Objective: Design \( K \) such that the closed loop system in Figure 2-11 is internally stable and such that:

\[
\lim_{n \to \infty} e(n) = \lim_{n \to \infty} [R(n) - G(K(e(n)))] = 0 \quad (2.35)
\]

for \( n = 0, 1, \ldots \) and for all \( G \in \mathcal{G} \).
Chapter 3

Controller Design and Implementation

The controller synthesis problem is clearly one of the most difficult and least understood issues in control theory. Even the synthesis of controllers for linear systems is generally hard when robust performance, not just stability, is the primary objective. This chapter presents a synthesis method leading to a nonlinear controller that is easily implemented and delivers robust asymptotic tracking. The approach taken is to:

- Linearize the process model $P_{NL}$,
- Find a continuous-time controller structure that delivers robust asymptotic tracking for the undelayed system,
- Use delay information to fix properties of the controller (gain, etc.),
- Use sampling information to approximate the continuous-time controller with a discrete-time equivalent.

3.1 Model Linearization

One approach to the synthesis problem is to make linear-control theory accessible by linearizing the process model. This approach seems particularly useful for the OMVPE control problem because performance issues (which are central to this problem since composition behavior is never captured by stability analysis alone) are not adequately addressed by the
existing nonlinear theory. Two approaches to linearization are to use Taylor-series expansion and ignore higher-order terms, or to invert the model.

3.1.1 Taylor-Series Expansion

The first, and most common, approach to linearizing a system is to approximate it by the first two terms in its Taylor-series expansion. Normally this expansion occurs at an equilibrium point of the system, although it is possible to expand about a nominal state and control trajectory.

Consider, first, expansion at an equilibrium point of the given system \( P_{NL} \):

\[
\dot{x}(t) = K_{gr} \begin{bmatrix} B_1 & B_2 \end{bmatrix} \begin{bmatrix} u_1(t) \\ u_2(t) \end{bmatrix} \tag{3.1}
\]

\[
\begin{bmatrix} y_1(t) \\ y_2(t) \end{bmatrix} = \begin{bmatrix} 1 & 0 \end{bmatrix} x(t) + \begin{bmatrix} 0 \\ \frac{K_cB_1u_1(t)}{B_2u_2(t)+K_cB_1u_1(t)} \end{bmatrix} \tag{3.2}
\]

Note that every state \( x \) is a potential equilibrium point, provided that:

\[
u_2 = -\frac{B_2}{B_1}u_1 \tag{3.3}\]

since this implies that:

\[
\dot{x} = K_{gr}(B_1u_1 - B_1u_1) = 0 \tag{3.4}\]

This condition can only be met, however, by \( u_2 = u_1 = 0 \), since physical constraints (captured by the saturation operator) prevent negative values of the controls. The state plays absolutely no role in linearizing this system since the only nonlinearity is manifested as a static function of the controls \( f : u \to y_2 \) (see Figure 3-1):

\[
y_2 = \frac{K_cB_1u_1}{B_2u_2 + K_cB_1u_1} \tag{3.5}\]

This function cannot be expanded about 0, however, since it is discontinuous at the origin:

\[
\lim_{u_1 \to 0^+} f(u) = 0, \quad u_2 = \epsilon > 0 \tag{3.6}\]
Figure 3-1: Process nonlinearity $f$ is a static function of the controls

$$\lim_{u_2 \to 0^+} f(u) = 1, \quad u_1 = \epsilon > 0$$ (3.7)

The other possibility would be to expand $f$ about a nominal trajectory $x^*(t), u^*(t)$. In general, such an expansion leads to a time-varying system; only when the nominal control trajectory is constant, i.e. $u^*(t) = u_o$, will the resulting approximation be linear time invariant (LTI). Since this time invariance property leads to a significantly easier problem (arbitrary time-varying problems are nearly as difficult as nonlinear problems), only expansion about such a trajectory $u_o$ will be considered. It is important to note, however, that specifying a desired composition ($y_2$) and thickness ($y_1$) is not sufficient to fix $u_o$; another specification, such as the desired growth rate $\dot{x} = G_R$, is needed. Figure 3-2 shows what typical trajectories may look like when a desired thickness, composition, and growth rate is specified. Calculating such trajectories requires the selection of nominal values of $K_{gr}$ and $K_c$, which may not be easy from available data, but otherwise is straightforward using the process model.

Once a nominal trajectory has been determined, expanding about it is easy, and doing so simply yields the plane tangent to $f$ at $u_o$ (Figure 3-3). The utility of such an approxima-
Figure 3-2: Taylor-series expansion can occur about a nominal trajectory.

...
Figure 3-3: Linearizing $f$ introduces significant modeling error for most compositions

In particular, note that:

1. The system is controllable from either $u_1$ or $u_2$,

2. There are more control inputs than states,

3. $y_2$ is a function of the controls independent of the system state,

4. The map $u \rightarrow y_2$ is not injective, i.e. fixing either $u_1$ or $u_2$, any $y_2$ can be reached from the remaining control.

These facts suggest that the process could be decoupled (i.e. one control could be used to control thickness while the other determines composition) and linearized by a static inversion of $f$, $F \equiv f^{-1}$. The fact that $F$ is static is extremely important to the utility of this approach, because static $F$ will commute with the delay and hold operators. Had feedback linearization been necessary, the process delay would pose a much more difficult problem.

Construction of $F$ is easy but requires the specification of a desired growth rate, $r$, desired composition, $\xi$, and nominal values of the parameters, $K_{gr}^0$ and $K_c^0$. Once these
values are determined the growth model becomes:

\[ r = K_{gr}^o \begin{bmatrix} B_1 & B_2 \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \]  

(3.8)

\[ \xi = \frac{K_c^o B_1 u_1}{B_2 u_2 + K_c^o B_1 u_1} \]  

(3.9)

which are simply two algebraic equations with two unknowns. Solving for \( u_1 \) and \( u_2 \) yields \( F : (r, \xi) \to (u_1, u_2) \) given by:

\[ u_1 = \frac{r \xi}{K_{gr}^o B_1 (\xi + K_c^o (1 - \xi))} \]  

(3.10)

\[ u_2 = \frac{r K_c^o (1 - \xi)}{K_{gr}^o B_2 (\xi + K_c^o (1 - \xi))} \]  

(3.11)

Considering, then, a nonlinear controller, \( K_{NL} \), with a particular Hammerstein structure, i.e. composed of a LTI dynamic system, \( K \), followed by the static nonlinearity, \( F \), suggests that \( K \) can be chosen based on the linearization of \( P_{NL} \), \( P = P_{NL}(F) \) (see Figures 3-4 and 3-5). \( P \) is not completely linear, though, since model uncertainty disturbs \( F \)'s inversion of \( P_{NL} \). Specifically, \( P \) is diagonal with its first element \( P_1 \) given by:

\[ \dot{x} = \begin{bmatrix} K_{gr}^o \\ K_{gr}^o \end{bmatrix} r \]  

(3.12)

\[ y_1 = x \]  

(3.13)

and its second element \( P_2 \) given by:

\[ y_2 = \frac{K_c \xi}{K_c^o + \xi (K_c - K_c^o)} \]  

(3.14)

As with the dynamic part of \( P_{NL} \), the dynamic relationship \( P_1 \) is uncertain but linear. The static map \( P_2 \) is almost linear, nevertheless it remains nonlinear except when \( K_c^o = K_c \). Figure 3-6 shows that for admissible values of \( \xi \), however, \( P_2 \) is nearly linear even with significant uncertainty in \( K_c \). Thus, although model inversion could not completely linearize the process, the resulting system \( P \) is linear enough to motivate linear synthesis techniques in the design of \( K \).
Figure 3-4: Decompose $K_{NL}$ into a linear dynamic system $K$ and static nonlinearity $F$

Figure 3-5: Linear $P$ allows $K$ to be chosen using linear design methodologies
Figure 3-6: Even with a 20% variation in $K_c$, $P_2$ is almost linear

### 3.2 Controller Design

Using model inversion to effectively linearize the process resulted in the added benefit of decoupling the control problem. Linear design methods can thus be used to independently develop a controller for each aspect of the process, thickness and composition control. This simplification from a Multi-Input Multi-Output (MIMO) nonlinear synthesis problem to two separate Single-Input Single-Output (SISO) linear design problems allows tremendous flexibility in the controller design.

The resulting controller, $K_{NL}$, will be nonlinear but will have a very special structure. Figure 3-4 shows that $K_{NL}$ can be decomposed into a linear dynamic system $K$ followed by a static nonlinear transformation (i.e. change of coordinates) $F$. Moreover, since the map $P$, composed of $F$ followed by $P_{NL}$, is decoupled (diagonal), $K$ will be diagonal with elements $K_1$, controlling thickness, and $K_2$, controlling composition. This section describes how $K_1$ and $K_2$ are chosen to provide stability and asymptotic tracking despite the model uncertainty, time delay, and sampled-data effects.
3.2.1 Thickness Control

The design of linear SISO controllers to achieve asymptotic tracking is a central theme of Classical Control Theory. Optimization Theory and other tools of Modern Control are therefore reserved for future work as data from this study allows the establishment of new performance specifications. The ideas of Bode, Nyquist, and Black will thus provide the backbone to solve the problem at hand.

![Block diagram](image)

Figure 3-7: $K_1$ is chosen so the closed-loop system tracks ramp commands

The first obvious requirement in the design of $K_1$ is a consequence of the Final Value Theorem; $K_1$ must contain an integrator for the closed-loop system to track ramp commands. This can be seen as follows. Define the Laplace Transform of $P_1$ as:

$$P_1(s) = \frac{\delta}{s}, \quad \delta = \frac{K_{gr}}{K_{gr}^o}$$

(3.15)

and the Laplace Transform of $K_1$ as:

$$K_1(s) = \frac{k}{s}$$

(3.16)

for some number $k$. Then the difference between a ramp command and the output of the closed loop system approaches zero:

$$\lim_{s \to 0} s \left( \frac{1}{s^2} - \frac{k\delta}{s^2 + k\delta s^2} \right) = \lim_{s \to 0} \frac{s}{s^2 + k\delta} = 0$$

(3.17)

Note that this result holds regardless of $\delta$, provided the closed loop system is stable.

A root locus (Figure 3-8) of this double-integrator system, $K_1P_1$, however, shows that stability is achieved for a positive gain $k$ only when $K_1$ introduces a zero in the open left-half plane (note that $\delta > 0$). The design issues, then, are 1) how to choose $K_{gr}^o$ (used in $F$), 2)
Figure 3-8: Root locus with a fourth order Pade approximation to a delay of 15 seconds

how to choose $k$, and 3) where to place the zero in $K_1$.

The choice of $K_{gr}^o$ certainly depends on available growth information, but it’s not clear
how to use that information. Post growth analysis can determine the average growth rate,
thus the effective value of $K_{gr}$ can be determined for previous (open-loop) runs. Neverthe-
less, this information gives only a range of values for a history of runs; it is not clear apriori
whether $K_{gr}^o$ should be chosen as the mean, median, or some other function of this data—or
whether it even matters. Defining:

$$\delta_{lo} = \frac{K_{gr-lo}}{K_{gr}^o}$$  \hspace{1cm} (3.18)

$$\delta_{hi} = \frac{K_{gr-hi}}{K_{gr}^o}$$  \hspace{1cm} (3.19)

it is clear that $\delta \in [\delta_{lo} \ \delta_{hi}]$ and that this is the uncertainty range that really matters;
choosing $K_{gr}^o$ to minimize this range reduces the effect of this uncertainty on the closed loop
system. $K_{gr}^o$ is thus set to $K_{gr-hi}$.

Although the choice of $k$ is not independent of the selection of a zero location, it is
assumed that the range of uncertainty on $\delta$ is small enough to allow separate decisions.
Given a zero location, then, $k$ ideally should be chosen so that $k\delta_o$, where $\delta_o = (\delta_{hi} - \delta_{lo})/2$,
places system poles near repeated values on the real axis. Such an assignment will guarantee
that the system will always be nearly critically damped—$\delta_{hi}$ slightly overdamping, and $\delta_{lo}$ slightly underdamping it. This critical damping will serve to keep overshoot and settling time from being unnecessarily bad.

The next issue, then, is the choice of zero location. Until now, all secondary issues such as time delay and sampled data effects have been ignored—if fact, the design process has occurred completely in continuous-time despite the fact that the controller $K_1$ will be a discrete-time system. This is because the primary effect of the sample-data structure of this problem is to increase the effective time delay [17], and time delay until now has not been an issue. In choosing a zero location, however, time delay must be considered because $k$ is fixed relative to it, and too high of a gain can drive the delayed system unstable (see Figure 3-8). Essentially, the design criterion is to choose the highest bandwidth zero such that the gain $k\delta_{hi}$ still does not drive unmodeled dynamics due to the delay unstable. Once the continuous-time controller is fixed, a discrete-time approximation can easily be determined with well known techniques such as forward difference, etc. Note also that since the actual choice of $k$ and the zero location are not independent issues (due to the unmodeled dynamics of the time delay), the actual values were chosen through trial-and-error via simulation.

3.2.2 Composition Control

Designing $K_2$ for composition control proceeds along much of the same lines as that for $K_1$. Essentially an integrator must be introduced for command following, and the controller gain $k$ is adjusted to the highest possible value that does not excite the unmodeled dynamics resulting from time delays.

![Diagram](image)

Figure 3-9: $K_2$ is chosen so the closed-loop system tracks step commands

Since the model uncertainty leaves $P_2$ nonlinear, however, Laplace techniques can not
be used to determine asymptotic properties. Rather, assuming $K_2 : ε → ξ$ of the form:

$$ξ(t) = k \int_0^∞ e(τ)dτ$$  \hspace{1cm} (3.20)

then the analysis of asymptotic properties is as follows:

$$R_2(t) - y_2(t) = \frac{1}{k} \dot{ξ}(t)$$  \hspace{1cm} (3.21)

$$⇒ R_2(t) - y_2(t) = \frac{(K_c - y_2(t)(K_c - K_o^2))K_o^2y_2(t) + (K_c - K_o^2)K_o^2y_2(t)y_2(t)}{k(K_c - y_2(t)(K_c - K_o^2))^2}$$  \hspace{1cm} (3.22)

$$⇒ R_2(t) - y_2(t) = \frac{K_cK_o^2y(t)}{k(K_c - y(t)(K_c - K_o^2))^2}$$  \hspace{1cm} (3.23)

where $ξ(0) = 0$. For step inputs we can consider the case when $R(t) = 0$, thus:

$$R_2 - y_2(t) = \frac{-K_cK_o}{k(K_c - y_2(t)(K_c - K_o^2))^2}(\dot{R}_2 - y_2(t))$$  \hspace{1cm} (3.24)

which has the form:

$$\dot{ε}_2(t) = -a(t)ε_2(t)$$  \hspace{1cm} (3.25)

$$⇒ ε_2(t) = ε_2^0 e^{\int_0^t -a(τ)dτ}$$  \hspace{1cm} (3.26)

Since $y(t)$ is always between 0 and 1 (admissible values resulting from the reflection of saturations on $u$ through $F$), $a(t)$ is a positive function with a clear lower bound $γ$, where $γ$ is given by:

$$γ = \frac{K_c - lo}{K_c - hi}$$  \hspace{1cm} (3.27)

Thus, considering the admissible values of $R_2 ∈ [0, 1]$, implying that $ε_2^0 ≥ 0$, it is clear that:

$$a(t) ≥ γ > 0 \quad ∀ t ≥ 0 \quad ⇒ \quad -\int_0^t a(τ)dτ ≤ -γt$$

$$⇒ \quad e^{\int_0^t a(τ)dτ} ≤ e^{-γt}$$

$$⇒ \quad |e^{\int_0^t a(τ)dτ}| ≤ |e^{-γt}|$$

$$⇒ \quad |e_2^0| |e^{\int_0^t a(τ)dτ}| ≤ |e_2^0| |e^{-γt}|$$

$$⇒ \quad |e_2(t)| ≤ |e_2^0| |e^{-γt}|$$
\[ \lim_{t \to \infty} |e_2(t)| = 0 \]

The error is thus a stable function asymptotically approaching zero, and, for step inputs, \( y_2 \) tracks \( R_2 \). Note that uncertainty will not affect the final value of \( y \)–only its rate of convergence—and stability is maintained provided \( K_c \) and \( K_c^o \) are positive.

Figure 3-10: Positive Nyquist plot of the integrator system distorted by a 15 second delay

The remaining design issue, then, is to select the controller gain \( k \). It is easy to see that, as one would expect in the linear system, a large gain promotes faster convergence. The caution, as in the design of \( K_1 \), is to avoid exciting unmodeled dynamics. Figure 3-10 shows the twisting of the nyquist plot caused by time delay, and it is clear that the infinite gain margin anticipated in a single integrator system is sacrificed by delay. Recalling the integrator structure of the controller (equation 3.20), and taking \( P_2 = 1 \), the transfer function \( K_2DP_2 \) of the forward loop becomes:

\[ L(s) = \frac{ke^{-\tau s}}{s} \quad (3.28) \]

Note that the \( e^{-\tau s} \) term appears since time delays must explicitly be accounted for to
compute the controller gain $k$, and this is the expression for the Laplace transform of a time delay. To calculate the frequencies when poles are crossing over the $j\omega$-axis, set $s = j\omega$ and use Euler's Identity to write:

$$L(j\omega) = \frac{k}{j\omega} [\cos(-\tau\omega) + j\sin(-\tau\omega)]$$  \hspace{1cm} (3.29)

From the Nyquist plot, it is clear that increasing $k$ will eventually cause the plot to intersect the $-1$ point i.e. the system has finite upward gain margin. The frequency $\omega^*$ at which this happens is a frequency such that $\cos(-\tau\omega^*) = 0$. This implies that $\omega^* = (n\pi)/(2\tau)$. The maximum gain before the system destabilizes, then, is given by:

$$\frac{k}{\omega^*} = -1 \quad \Rightarrow \quad k = \frac{\pi}{2\tau}$$  \hspace{1cm} (3.30)

### 3.3 Simulation Study

After some trial-and-error, the controller design $K_1$ that was chosen is given by:

$$x[n + 1] = x[n] + (.0001)e_1$$  \hspace{1cm} (3.31)

$$r = x[n] + (.01)e_1$$  \hspace{1cm} (3.32)

Likewise, the controller $K_2$ is given by:

$$x[n + 1] = x[n] + (.02)e_1$$  \hspace{1cm} (3.33)

$$\xi = x[n]$$  \hspace{1cm} (3.34)

These designs were simulated on Simulink 1.3 under various conditions. Parameters were selected as outlined in Table 3.1.

It is clear from the simulations that the specified controller achieves asymptotic tracking and significantly improves performance over open-loop operation—even when significant sensor noise and parameter uncertainty is present. Robustness was verified by extensive simulation (not shown) over the uncertainty set. Figure 3-11 shows open loop results for the parameter specifications outlined in Table 3.1. Not surprisingly, performance suffers considerably when $K_{gr}$ and $K_c$ are unknown. In Figure 3-12, however, it is clear that clos-
<table>
<thead>
<tr>
<th>Description</th>
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</tr>
<tr>
<td>Delay</td>
<td>$\tau$</td>
<td>15 sec</td>
</tr>
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<td>AI growth coefficient</td>
<td>$B_1$</td>
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</tr>
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<td>Ga growth coefficient</td>
<td>$B_2$</td>
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<tr>
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<td>$K_{gr}^o$</td>
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<td>Simulated value $K_{gr}$</td>
<td>$K_{gr}$</td>
<td>4</td>
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<tr>
<td>Range of $K_c$</td>
<td>$[K_{c-lo} \ K_{c-hi}]$</td>
<td>[.8 1.2]</td>
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<tr>
<td>Saturation on $u_2$</td>
<td>$[u_{min}^2 \ u_{max}^2]$</td>
<td>[0 19]</td>
</tr>
</tbody>
</table>

Table 3.1: Model parameter specifications

ing the loop tremendously enhances this performance—even when the noise shown in Figure 3-13 is superimposed on the measurement. Figure 3-14 shows the control signals needed to produce these results. Clearly the feedforward term in $K_1$ is contributing to the high frequency variations in $u_1$ and $u_2$. Figure 3-15 summarizes these results by contrasting open and closed loop results.

Although successful closed loop responses have been demonstrated for structures involving films with thicknesses on the order of 0.1 microns (1000 Angstroms), typical quantum-well devices need the capability of controlling the growth of films on the order 100 Angstroms. Figure 3-16 shows that good performance can be achieved for this class of reference commands, although delays in the system certainly impose fundamental limits on achievable performance. The structure shown is a GRINSCH quantum-well laser, with the second figure overlaying quantum wells to contrast performance.

Simulation also suggested the relative stability of the closed loop system even when $K_{gr}$ and $K_c$ are allowed to vary with time (Figure 3-17). Although such a test is not a substitute for rigorous analysis, and there probably does exist a trajectory $K_{gr}^*(t)$ and $K_c^*(t)$ that will drive the system unstable, it bolsters confidence that real-time experiments will probably not damage equipment even if the parameters change mid-growth.

Finally, Figure 3-18 shows the verge of instability broached by increasing the gain of $K_2$ to $\pi/2\tau$. All together, these results verify the analysis of the previous sections, and encourage the use of the controller in actual real-time experiments.
Figure 3-11: Simulation of open loop performance

Figure 3-12: Simulation of closed loop performance
Figure 3-13: Simulated noise on the sensor measurements

Figure 3-14: Closed loop control signals
Figure 3-15: Closed loop significantly improves over open loop growth

Figure 3-16: Simulated growth of a GRINSCH quantum-well laser structure
Figure 3-17: Results of time variations in $K_{gr}$ and $K_c$

Figure 3-18: Verge of instability verified by simulation
3.4 Experimental Results

Three experiments were performed to test the actual utility of the controller design. These tests recorded the measurements from the ellipsometer, which include sensor noise, but they do not allow for independent post-growth measurement to reconstruct the actual thickness and composition as a function of time.

The first experiment tested $K_2$ by forcing the controller to compensate for erroneous control setpoints (Figures 3-19 and 3-20). If allowed to run open loop, the composition would have alternated between approximately 60% and 30% aluminum. The target values, however, were 50% and 40%, respectively. Results of the experiment indicate that the controller does, in fact, asymptotically track target compositions despite erroneous setpoints.

This experiment also revealed, however, distinct oscillations resulting from unmodeled dynamics in the process. It was not clear, however, whether these dynamics are in the growth process—in which case they affect the actual output and should be eliminated—or whether they result from the ellipsometer’s fitting algorithm. If they are the result of the fitting algorithm, however, examination of the mean square error (MSE) of the fit during growth would make this apparent. Another experiment was therefore planned to determine the nature of these oscillations.

The next experiment repeated a test of the composition controller by directly comparing open and closed loop performance. In this run, the control setpoints were calculated to deliver the desired structure. The first half of the run grew this structure open loop, and then the structure was repeated closed loop for direct comparison. During growth, the ellipsometer’s MSE was monitored closely, and it was noticed that the error jumps significantly at every interface before it settles to a reasonable value. Data from the run (Figures 3-21 and 3-22) show that oscillations were only present while the MSE was unreasonably high—the conclusion being that the unmodeled dynamics are an artifact of the fitting algorithm.

Comparing open and closed loop growth, however, shows significant improvement and asymptotic tracking in closed loop. It also seems as though integrator wind-up is an issue, since $u_2$ is saturated much of the time. For growth rates larger than 10 Angstroms/sec, then, the mass flow controller on the gallium line should be upgraded to preserve performance. If this is too expensive, then various anti-wind-up strategies exist that can enhance performance [32].
Figure 3-19: Run M792: Feedback enabled at 500 seconds

Figure 3-20: Run M792: Controller tracks composition despite erroneous control setpoints
Figure 3-21: Run M799: Feedback enabled at 2350 seconds

Figure 3-22: Run M799: Controller tracks composition despite saturating controls
The final experiment was designed to test thickness control; but the ellipsometer had trouble measuring thickness for AlGaAs with the existing database and fitting routine. GaAs was therefore grown on a buffer layer of 60% AlGaAs. Although the control setpoints were fixed, calculated to grow at a rate of 3 Angstroms/sec, the target growth rate was stepped from 3 to 6 and back to 3 Angstroms/sec. Results (Figures 3-23 and 3-24) clearly verify asymptotic tracking, but a subtle oscillation is also present. Unlike the oscillations in previous runs, however, this one is at a lower frequency, and it clearly is unstable.

Since unstable dynamics in the process would have manifest in previous runs, the two explanations for this oscillation are either 1) The unmodeled dynamics of the ellipsometer (identified in composition experiments) grow with the MSE (which grows without bound as the film becomes optically thick), or 2) the closed loop is unstable. This instability could result if the actual $K_{gr}$ is larger than the allowed values in the uncertainty model (i.e. $K_{gr} > K_{gr-hi}$), thus exciting unmodeled dynamics. Although simulation suggests this is not the case, and the first explanation seems more reasonable, data from this run alone is not conclusive.

Altogether, these experiments indicate that the design methodology, using $F$ to invert $P_{NL}$, is useful and that the proposed controller does, in fact, deliver robust performance. Directions for further research are discussed next in Chapter 4.
Figure 3-23: Run M7106: It becomes increasingly harder to measure the thick film

Figure 3-24: Run M799: Feedback enabled at 1000 seconds
Chapter 4

Conclusion

4.1 Summary

This research spearheaded an analysis of feedback's potential for improving the repeatability of OMVPE. Focusing on AlGaAs as a material system, spectroscopic ellipsometry was used to measure film thickness and composition for real-time control. To accomplish this, a process model was developed using flow rates of the group III precursors as control inputs while maintaining reactor pressure and temperature in the mass-transport limited growth regime.

It was found that error propagation in the ellipsometer's signal processing algorithm prevented simultaneous extraction of thickness and composition information from the measured data. Nevertheless, a synthesis procedure was developed that effectively linearized and decoupled the process model, allowing independent designs for thickness and composition control. With the transformation of the MIMO nonlinear synthesis problem to two independent SISO linear design problems, frequency domain ideas easily lead to the design of a controller delivering robust asymptotic tracking despite time delay in the loop.

Experimental data confirmed the results of simulation, and the controller succeeded in tracking both composition and thickness, albeit in separate experiments. Unmodeled dynamics are apparent in the experimental data, although it is not clear whether they are due to the process—thus affecting the actual film properties—or simply a fabrication of the ellipsometer's regression procedure. Analysis of composition control experiments suggest these dynamics are an artifact of the ellipsometer's estimation algorithm, but conclusive data for thickness control is not available.
4.2 Directions of Future Research

Efforts to extend this work should evolve in three directions. First, measurement reliability needs to improve. Second, the controller design should be optimized, and third, the class of material systems approximated by the model must be expanded.

Measurement reliability can be enhanced in at least two ways. The first is obvious and widely accepted by the materials-science community: spectroscopic ellipsometry should be used in conjunction with another sensing mechanism, such as optical reflectance. This synergistic role of a duplicate sensor is important to independently measure optical properties of the growing film, thus facilitating direct extraction of thickness and composition. A second sensor can also be used to expand the range of operation to thick films where ellipsometry fails. Another way to enhance measurement reliability is to improve the extraction methods used to estimate thickness or composition from $\Psi$ and $\Delta$ measurements. One idea is to invoke linear systems theory, motivated by the exponential spirals characteristic of ellipsometry, and use system identification techniques to recursively estimate film properties. Another is to generate an error of the measured $\Psi$ and $\Delta$ data from a reference trajectory and modify the control algorithm to consider this error directly.

Although this research succeeded in establishing a performance baseline of robust asymptotic tracking, it is certainly worthwhile to investigate achievable performance limits with controller optimization. An understanding of such limits requires a reformulation of the control problem, optimization of an appropriate induced-norm, and the definition of an appropriate uncertainty set. If the Hammerstein controller structure proposed in this work is used, and an analysis of the unmodeled dynamics in the system suggests the decoupling assumption is valid, separate performance criteria can be established for the design of $K_1$ and $K_2$. This establishment of separate performance criteria can be extremely useful in deciding how to best allocate control authority to meet particular device specifications.

Finally, if feedback is going to actually improve the utility of OMMPE as a manufacturing process, the material systems compatible with closed loop growth must be expanded to keep the process as versatile as possible. This will not only require the establishment of an appropriate library of optical constants for ellipsometric measurements, but a new growth model must be developed to incorporate quaternary compounds. This development is a nontrivial extension of the model presented in this research for a number of reasons. First,
quaternary compounds have two composition parameters to monitor and control accurately (e.g. $In_xAl_{1-x}As_yP_{1-y}$ or $In_xAl_yGa_{1-x-y}As$). Also, these solid-phase composition parameters are, unlike AlGaAs, not generally a linear function the vapor-phase concentration of their respective reactants. This effectively makes the parameter $K_c$ used in this study a function of $B1$ and $B2$. Moreover, the uncertain parameters $K_{gr}$ and $K_c$ will not just vary with vapor-phase concentration, but they also become dependent—and even sensitive—to the growth temperature. The fact that the controller developed in this study maintained stability even when $K_{gr}$ and $K_c$ were allowed to fluctuate, however, inspires an optimistic evaluation of feedback’s potential to repeatably grow even quaternary compounds, and to significantly improve the efficiency of OMVPE.
References


