


# Chapter 15

## Progress in Optimization of Physical Vapor Deposition of Thin Films


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### ABSTRACT

*In this chapter, the current state of the art in optimization of thin film deposition processes is discussed. Based on the reliable and credible published results, the study aims to identify the applications of various optimization techniques in the thin film deposition processes, with emphasis on physical deposition methods. These methods are chosen due to their attractive attributes over chemical deposition techniques for thin film manufacturing. The study identifies the critical parameters and factors, which are significant in designing of the optimization algorithms based on the specific deposition methods. Based on the specific optimization studies, the chapter provides general trends, optimization evaluation criteria, and input-output parameter relationships on thin film deposition. Research gaps and directions for future studies on optimization of physical vapor deposition methods for thin film manufacturing are provided.*

### INTRODUCTION

There is increasing need for nano-sized materials for applications in various fields such as optical, microelectronics, solar, optoelectronic, dielectrics, biomedical, etc. (Jilani, Abdel-wahab, & Hammad,

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2017; Mwema, Oladijo, Akinlabi, & Akinlabi, 2018). This need has led to emergence of new class of materials known as thin films (their thickness vary between nanometers to micrometers), which have proved superior in terms of properties and performance over the bulk materials (Jilani et al., 2017). The methods of manufacturing thin film materials are broadly classified into physical and chemical deposition methods. The chemical deposition methods depend on the chemistry of the solutions used and chemical reactions are involved during formation of the thin film materials. There are several chemical methods of depositing thin films, some of which include plating, chemical bath, sol-gel, chemical vapor deposition, CVD (atomic layer deposition, low pressure, etc.) (Sivaram, 1995). Physical deposition methods involve dislodging of material from source and condensing them on a surface of a substrate and the process mostly occurs inside a vacuum. Some of the physical methods include evaporation methods (vacuum thermal, electron beam, ion plating, laser beam, etc.) and sputtering techniques (Mwema et al., 2018; Semaltianos, 2001; Simon, 2018). The preference of the physical methods is based on their capability to produce quality films and flexibility in terms of processing parameters.

There are various parameters governing the deposition of thin films through physical methods. While some of the methods are specific to the methods, the physical methods share common parameters such as time, rate of deposition, vacuum pressure, material deposition yield, temperature, and so on (Mwema et al., 2018). The interrelationships among these parameters and their influence on the quality of the thin films is complex. As such, several studies have reported on the effect of various deposition parameters to the properties of various thin films (Azmand & Kafashan, 2019; Gullu, Isik, & Gasanly, 2018; Khalaf, Al-Taay, & Ali, 2017; Mwema, Oladijo, & Akinlabi, 2018; Mwema, Akinlabi, & Oladijo, 2019; Mwema, Akinlabi, Oladijo, & Dutta Majumdar, 2019; Tondare, Shivaraj, Narasimhamurthy, Krishna, & Subramanyam, 2018). These studies have demonstrated that the choice of deposition parameters is critical for specific performance, quality and applications of the thin films. The quality of the deposited films can be measured by the level of defects such as cracks, porosity, and so forth and these defects significantly depend on the deposition parameters. Readers are referred to a recent review outlining the relationship between porosity and plasma-spray coating process (Odhiambo, Li, Zhao, & Li, 2019). The deposition parameters determine the kinetics of material source removal, transport, diffusion and growth of the thin films.

The purpose of this chapter is to discuss the progress in research on the optimization of physical deposition of thin films. The parameters influencing these methods, optimization methods and summary of the recent studies on the subject are described. The article is an important resource for selection and optimization of parameters during physical deposition of thin films.

## **OPTIMIZATION IN THIN FILM TECHNOLOGY**

### **Parameters in Physical Deposition of Thin Films**

Physical deposition methods involves evaporation and sputtering techniques (Jilani et al., 2017). In general, both techniques involve removal of the coating material from the source (target) and depositing it onto a surface (substrate). The processes involved in physical deposition of thin films can be summarized in Figure 1. In evaporation processes, the source material is usually heated until it boils and vaporizes. The source of heat maybe resistive heater or e-beam evaporator (Quero, Perdigones, & Aracil, 2018). The evaporated material is transported or accelerated, through vacuum chamber, to the substrate

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