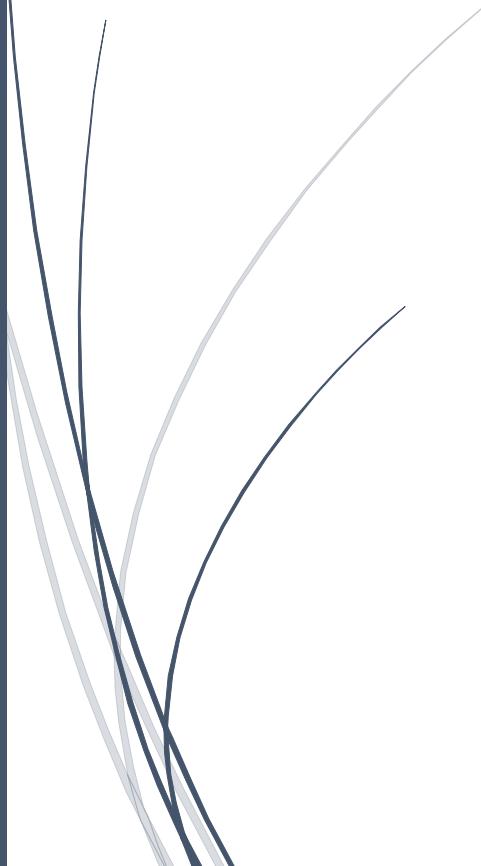


Applied Mathematics for AI and Engineering Problem Solving



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Abstract

This chapter explores the application of advanced mathematical models in Artificial Intelligence (AI) and engineering problem solving, focusing on key areas such as optimization, stochastic modeling, and real-time system control. By integrating mathematical techniques like linear algebra, calculus, and probabilistic models, AI systems can be designed to solve complex, dynamic, and uncertain problems across various engineering domains. The chapter delves into the use of optimization methods for AI system design, including parameter tuning and model selection, to ensure the efficiency and adaptability of intelligent systems. Additionally, the role of stochastic models in geospatial engineering is examined, highlighting the power of random fields and spatial statistics for modeling spatial dependencies and improving predictive accuracy in environmental, urban, and resource management. The integration of these mathematical methods with machine learning algorithms and control theory enhances the performance of AI systems in real-time applications, such as autonomous systems and dynamic decision-making processes. This chapter presents a comprehensive framework for understanding how mathematical optimization and probabilistic modeling can drive advancements in AI and engineering, providing novel solutions to some of the most pressing challenges in modern technology.

Keywords: Mathematical Optimization, AI System Design, Parameter Tuning, Stochastic Models, Random Fields, Geospatial Engineering.

Introduction

The integration of mathematical models in Artificial Intelligence (AI) and engineering problem solving has become an essential driver of technological progress [1]. AI, when combined with advanced mathematical techniques, offers a robust framework for addressing complex and dynamic challenges that span a wide range of engineering domains [2]. Mathematical models provide the foundational tools for AI systems to process large datasets, optimize solutions, and make informed decisions in real-time [3]. These models, rooted in disciplines such as calculus, linear algebra, probability theory, and optimization, allow AI to simulate, predict, and control systems that are both uncertain and intricate [4]. Whether it is optimizing resource allocation in manufacturing or modeling environmental conditions for urban planning, mathematical techniques help engineers and data scientists design intelligent systems that are efficient, reliable, and adaptable to varying scenarios [5].

In AI system design, optimization plays a critical role in ensuring that machine learning models achieve their highest potential [6]. One of the most significant aspects of optimization is parameter tuning, where a model's hyperparameters are adjusted to improve performance [7]. These parameters, such as learning rates or regularization coefficients, govern how a model learns and adapts to data [8]. The tuning process requires iterative testing, often guided by optimization techniques like grid search or Bayesian optimization [9]. The goal is to find the configuration that yields the most accurate predictions while avoiding overfitting or underfitting. For complex AI systems, selecting the appropriate model architecture is equally crucial. This decision depends on the problem at hand, the data available, and the trade-offs between model complexity and interpretability [10].

Probabilistic models are another integral component of AI system design, especially when it comes to handling uncertainty and variability in data [11]. These models are based on principles of probability theory and are widely used in AI applications like machine learning, decision-making, and predictive analytics [12]. By quantifying uncertainty and updating beliefs in response to new data, probabilistic models help AI systems make informed decisions even in the face of incomplete or noisy data [13]. For instance, Bayesian networks provide a graphical representation of probabilistic relationships among variables, allowing AI systems to infer the most likely outcomes based on prior knowledge and observed evidence [14]. This capability is critical in fields such as healthcare, where AI systems must make decisions based on uncertain or limited medical data [15].