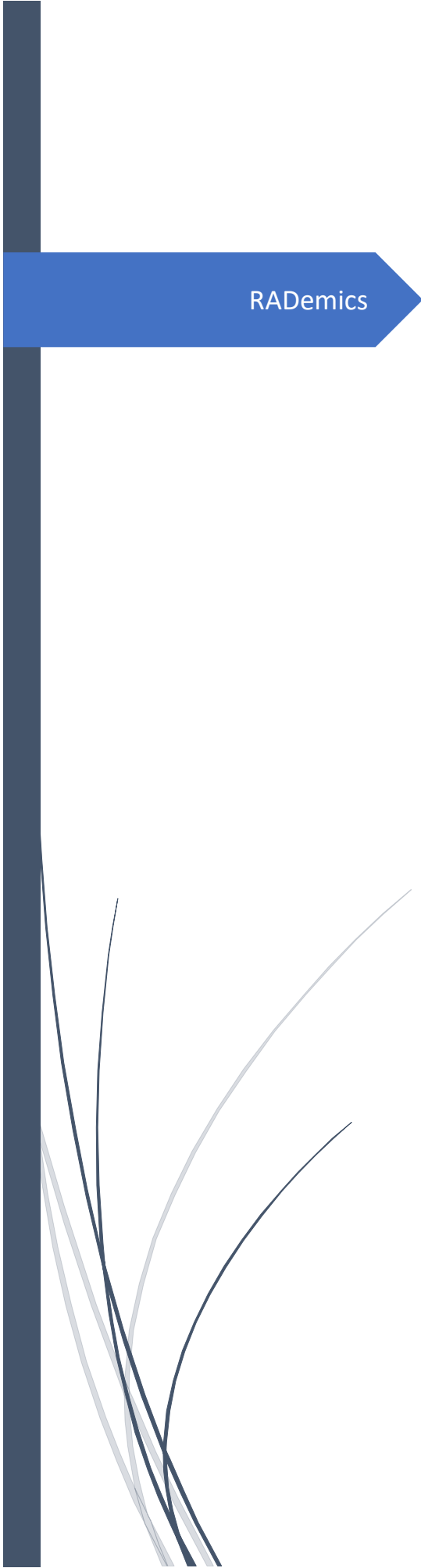




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Hybrid Deep Learning and Evolutionary Algorithms for Multivariate Time Series Forecasting in Industrial Applications

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Abstract

The increasing complexity and dynamic nature of industrial systems have elevated the importance of accurate multivariate time series forecasting for critical functions such as predictive maintenance, anomaly detection, process optimization, and operational planning. Traditional deep learning approaches, while powerful in capturing non-linear temporal dependencies, face significant limitations in real-time environments due to their computational demands, sensitivity to hyperparameter configurations, and lack of adaptability. To address these challenges, this chapter presents a comprehensive study on hybrid deep learning and evolutionary algorithm frameworks, designed to enhance forecasting accuracy, robustness, and real-time adaptability in industrial applications. The proposed hybrid architectures leverage the temporal modeling strengths of deep networks and the global optimization capabilities of evolutionary algorithms to automate hyperparameter tuning, improve generalization, and adapt to concept drift in streaming data. Comparative evaluations with non-hybrid models highlight the superior performance of hybrid methods in terms of accuracy, fault tolerance, and computational efficiency. Emphasis is also placed on the practical deployment of these models in live industrial settings, focusing on their ability to maintain reliability under data noise, sensor faults, and dynamic operational conditions. This chapter contributes to the advancement of intelligent, resilient, and scalable forecasting systems tailored for Industry 4.0 environments.

Keywords:

Multivariate Time Series, Deep Learning, Evolutionary Algorithms, Real-Time Forecasting, Fault Tolerance, Industrial AI

Introduction

Advancements in automation, cyber-physical infrastructure, and sensor technologies [1], [2]. These systems generate high-dimensional, multivariate time series data that evolve over time,

often reflecting intricate dependencies across operational processes. Accurate forecasting of such time-dependent data is essential for critical functions such as condition monitoring, quality control, demand planning, and fault detection [3]. Forecasting in industrial settings is far more challenging than in conventional applications due to the presence of non-stationary patterns, noise, missing values, and the need for timely prediction [4]. Traditional statistical forecasting models, including ARIMA, VAR, and exponential smoothing techniques, often fall short in modeling the non-linear dynamics and complex inter-variable relationships prevalent in industrial data streams [5]. As a result, there is a growing shift toward more intelligent, adaptive, and scalable forecasting approaches that can cope with the demanding nature of industrial environments.

Deep learning has emerged as a powerful tool in time series forecasting, particularly with the adoption of architectures such as Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Temporal Convolutional Networks (TCNs) [6]. These models can learn rich temporal patterns and long-term dependencies, making them well-suited for multivariate industrial datasets. Despite their advantages, standalone deep learning models exhibit several limitations when applied in real-time industrial contexts [7]. These include high computational costs, sensitivity to hyperparameter tuning, risk of overfitting, and limited adaptability to dynamic changes in data distributions. Such models often function as black boxes, offering limited interpretability—an important consideration in safety-critical industrial applications [8]. Consequently, while deep learning models represent a significant advancement over classical techniques, their direct application in operational industrial systems demands further enhancement in terms of performance, flexibility, and transparency.

To bridge these gaps, hybrid approaches that combine deep learning with evolutionary algorithms have gained considerable attention [9]. Evolutionary algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE) are inspired by biological processes and natural selection [10]. These algorithms are capable of efficiently navigating complex and high-dimensional optimization spaces [11]. When integrated with deep learning architectures, they can automate the search for optimal model configurations, including hyperparameter tuning, feature selection, and architecture refinement [12]. This synergy enables hybrid models to achieve improved forecasting accuracy, faster convergence, and greater adaptability to changing industrial conditions [13]. The optimization process can be continuously refined in real-time or batch settings, allowing the forecasting model to remain relevant and accurate despite evolving system dynamics or unexpected anomalies in the data [14].