

# Physics-Informed Machine Learning Digital Twin for Thermal Turbulent Jet Temperature Prediction

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## Abstract

*Keywords:*

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## 1. Introduction

## 2. Related Work

The concept of Digital Twin (DT) has evolved dramatically from its initial conceptualization to become a cornerstone of Industry 4.0. The foundational work introducing DTs in the context of NASA and Air Force vehicles [1] established the groundwork for virtual system replication, which was further developed through emphasis on manufacturing autonomy [2]. The theoretical understanding expanded through comprehensive reviews examining semantic construction applications [3] and manufacturing implementations [4]. Integration of DTs into cyber-physical production systems [5] marked a significant advancement in industrial applications, building upon initial product lifecycle management concepts [6]. This theoretical framework was enhanced by establishing correlations between digital twins and cyber-physical systems, particularly in smart manufacturing contexts [7], leading to refined distinctions between models and digital twins [8]. Subsequent work has focused on characterizing digital twins [9], establishing standardization approaches [10], and developing frameworks for implementation [11].

As the theoretical foundation of digital twins matured, industrial applications began demonstrating significant practical impact across various sectors.

Manufacturing processes involving complex systems have seen extensive DT implementation [12], while comprehensive reviews have documented applications across diverse industries [13]. The construction industry has benefited from these developments through building system optimization [14, 15], and the energy sector has particularly advanced through DT implementation in power plant systems [16]. Maintenance applications have shown significant progress [17], with data fusion playing a crucial role in predictive maintenance strategies [18]. Digital twin networks have emerged as a crucial development [19], enabling better integration and communication between different system components [20].

The transition from industrial applications to more sophisticated modeling approaches has been marked by significant developments in physics-based digital twins. Component-based reduced-order models [21] have enhanced system modeling capabilities, while the integration of machine learning with physics-based modeling has shown promising results [22]. Advanced frameworks combining neural networks with physics-based models [23] have improved prediction accuracy, and physics-based digital twins have been successfully implemented in predictive control systems [24]. These developments have particularly benefited thermal and fluid systems, where physics-based modeling is essential for accurate system representation [25, 26].

Building upon these physics-based foundations, fluid mechanics applications of digital twins have evolved to handle increasingly complex systems. The simulation aspects of digital twins [27] provided a crucial framework for fluid dynamics applications, which has been further refined through various modeling approaches [28]. Machine learning-based digital twins for dynamical systems [29] and physics-based compressive sensing [30] have enhanced the capability to model complex fluid behaviors. Digital twin modeling techniques have advanced significantly [31], incorporating both data-driven and physics-based approaches [32]. These advancements have enabled more accurate representation of complex flow phenomena [33], particularly beneficial for turbulent jet applications.

The integration of Computational Fluid Dynamics (CFD) with digital twins represents perhaps the most significant advancement for applications involving complex flow systems. The combination of data analytics with CFD models [34] has enhanced the ability to simulate and predict complex flow behaviors. Specific applications in fluid blending [35] and combustion systems [36] have demonstrated the effectiveness of CFD-based digital twins in handling complex flow phenomena. Recent developments in CFD-FEM

integration [37] have further expanded the capabilities of digital twins in modeling high-temperature applications. The advancement of simulation techniques [38] and integration with machine learning [39] has particularly benefited applications involving turbulent flows and heat transfer [40].

The present work on developing a digital twin for thermal turbulent jets builds upon these foundational developments while addressing several key challenges identified in the literature. Our approach combines the robust physics-based modeling demonstrated in recent studies with advanced machine learning techniques to enhance prediction accuracy in turbulent flow conditions. By integrating CFD simulations with real-time data analytics, our work addresses the need for improved modeling of multi-scale phenomena in turbulent flows while maintaining computational efficiency.

The field continues to evolve, with recent developments focusing on industry-specific applications [41, 15] and enhanced modeling capabilities [42]. Current challenges in applying digital twins to thermal turbulent jets include the need for enhanced real-time data integration, improved handling of multi-scale phenomena, and more robust approaches for combining physics-based models with machine learning techniques. These challenges, particularly relevant to high-temperature flows and turbulent conditions, present opportunities for advancing the field. Our work specifically addresses these gaps by developing an integrated approach that leverages the strengths of both physics-based modeling and machine learning to improve the accuracy and reliability of turbulent jet simulation and control.

### **3. TurbTwin: An AI-Driven Digital Twin Framework for Thermal Turbulent Jet Simulation**

In this section, we introduce TurbTwin, an AI-driven digital twin framework for thermal turbulent jet simulation, comprising the Physical Twin and Digital Twin. The Physical Twin is the real-world experimental setup with advanced instrumentation for data acquisition and monitoring, while the Digital Twin integrates physics-based simulations and AI-driven models for analysis and prediction. Figure 1 illustrates the framework’s architecture and component interactions.

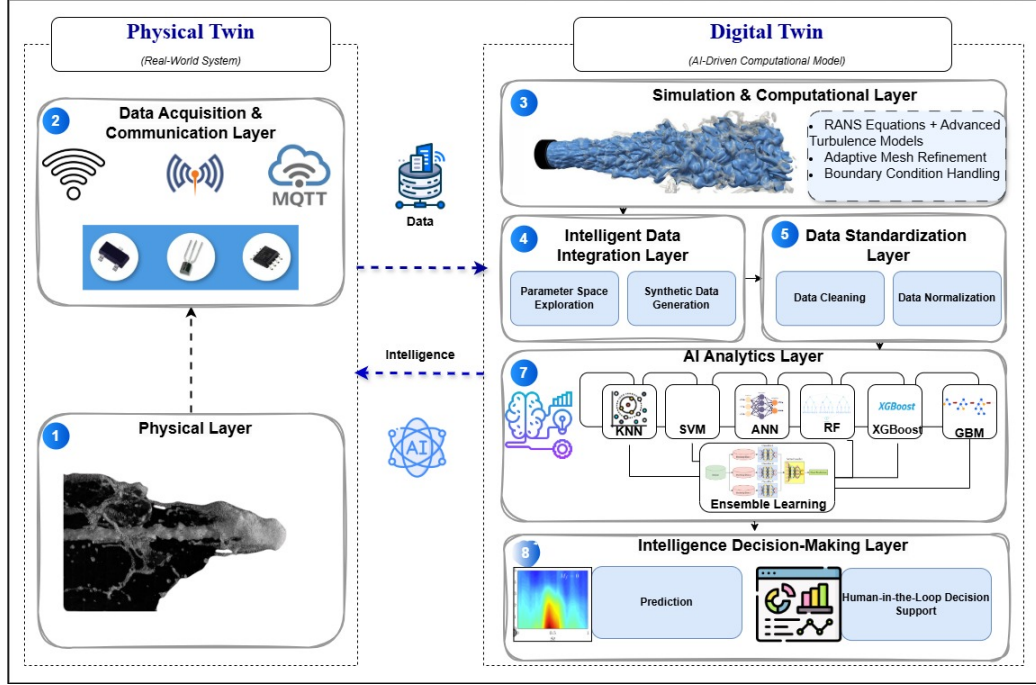


Figure 1: TurbTwin Architectural Framework

### 3.1. Framework Architecture Overview

#### 3.1.1. Physical Twin (Real-World System)

The Physical Twin serves as the foundational entity for the integration of cyber-physical systems, consisting of two distinct layers: the physical layer and the data acquisition and communication layer.

- **Physical layer:** represents the core components of the system, including the experimental setup designed to investigate turbulent jet dynamics. This layer includes a thermally insulated cylindrical tank equipped with various measurement instruments, such as K-type thermocouples for temperature monitoring and dedicated inlet and outlet pipes for controlling fluid flow. The physical layer provides the real-world environment for the experiments.

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- **Data acquisition and communication layer :** serves as a critical component that enables continuous monitoring, processing, and transmission of data between the physical layer and the virtual domain. This

layer integrates a high-fidelity data acquisition system (DAQ) that collects data from a range of sensors, including thermocouples, pressure transducers, and flow meters. The system employs robust communication protocols, such as Modbus and Ethernet/IP, to ensure real-time transmission of data. This layer ensures seamless interaction between the physical and virtual systems, providing real-time insights into the experimental setup.

The integration of these two layers allows for precise control and observation of the physical system, with the resulting output being a detailed dataset for further analysis and modeling.

### 3.2. Digital Twin

The Digital Twin represents the computational counterpart of the Physical Twin, operating as a sophisticated simulation environment that integrates physics-based models and AI-driven algorithms for predictive analysis and system optimization.

- **Simulation and computational layer:** The Virtual Twin simulates the physical system using advanced numerical models, primarily based on the Reynolds-Averaged Navier-Stokes (RANS) equations, which govern the turbulent flow dynamics within the system. To accurately represent complex flow phenomena, the simulation incorporates state-of-the-art turbulence modeling techniques, such as k- or Large Eddy Simulation (LES). The computational domain is typically a 2D axisymmetric model, carefully designed to mirror the geometry and operational conditions of the physical system.

The simulation leverages finite volume methods (FVM) for discretization, ensuring accurate solution representation across the computational domain. Advanced numerical schemes, including segregated implicit solvers and pressure-velocity coupling algorithms, are employed to ensure robust solution convergence. The framework supports the use of adaptive mesh refinement (AMR) and multi-physics coupling, enabling detailed capturing of fluid dynamics, heat transfer, and other phenomena under varying operating conditions.

The simulation layer is designed to support both steady-state and transient simulations, facilitating the exploration of dynamic system responses over time. Additionally, it is equipped with automated work-

flows for parameter variation studies, enabling a comprehensive understanding of the system's behavior across different operational scenarios. This computational infrastructure emphasizes numerical efficiency, accuracy, and systematic validation protocols to maintain high-fidelity simulation results, bridging the gap between physical measurements and predictive modeling.

## • **Intelligent Data Integration Layer**

The Intelligent Data Integration Layer acts as a bridge between physics-based simulations and machine learning models in the digital twin framework. Its main role is to automate the generation of large-scale datasets by collecting and organizing relevant physical data from simulations. This layer ensures the consistency, quality, and traceability of the data, making it ready for analysis and integration into machine learning models. The process of Intelligent Data Integration enables the generation of synthetic data crucial for the development of the digital twin framework. The following steps outline the systematic approach for generating large-scale datasets, essential for integrating physics-based simulations with machine learning models.

### 1. **Define Simulation Parameters**

Set the operational parameters, such as temperature, pressure, and fluid flow, which define the conditions under which the system operates.

### 2. **Run Automated Simulations**

Execute simulations utilizing CFD models. This step involves varying key parameters to explore the different behaviors of the system under diverse operating conditions.

### 3. **Activate Data Collection Pipelines**

Automatically extract relevant physical quantities, such as temperature, velocity, and pressure, from the simulation results. These data points are essential for further analysis and model training.

### 4. **Ensure Data Quality**

Implement automated quality assurance mechanisms that validate the consistency, accuracy, and completeness of the collected data. This ensures high-quality data throughout the data collection process.

## 5. Store Data in Structured Formats

Organize and store the collected data in structured and efficient formats, to facilitate easy access and retrieval for further analysis.

## 6. Automate Data Labeling and Tracking

Label the collected data with metadata, such as simulation conditions and parameters, and track the provenance of each data point. This ensures traceability and proper context for each dataset across different simulation scenarios.

- **Data Standardization Layer** The Data Standardization Layer is a crucial preprocessing component in the digital twin architecture, ensuring data consistency and compatibility for machine learning. It involves three primary transformations: unscaled data preservation, which maintains the original physical meaning of the data; standardization, which establishes uniform statistical properties across datasets; and normalization, which optimizes the data for improved algorithm performance. Automated pipelines are employed to ensure consistent data representation across various scales and units, allowing for seamless integration of data from physical sensors and numerical simulations. This layer plays a key role in enhancing model training by preserving data relationships while optimizing the effectiveness of machine learning models.

- **Predictive Analytics Layer**

- **Intelligence Decision-Making Layer**

### 3.3. Ensemble Learning

## 4. Evaluation and Experimental Results

This section provides an overview of the implementation and evaluation process of the proposed framework. It covers the experimental setup, including the tools and environment used, followed by a description of the datasets and their preparation. Next, the experimental results are presented, demonstrating the framework's performance. Finally, a comparative analysis is conducted to benchmark the approach against state-of-the-art methods, highlighting its strengths.

213 4.1. *Ensemble Based Machine Learning and Deep Learning*

214 4.2. *Experimental Setup*

215 4.3. *Dataset*

216 4.4. *Data Preprocessing*

217 4.5. *Model Performance Evaluation*

218 4.6. *Comparative Analysis with Existing Methods*

219 4.7. *Case Study*

## 220 5. Conclusions

221 *Declaration of generative AI and AI-assisted technologies in the writing pro-*  
222 *cess:*

223 During the preparation of this work, the author used ChatGPT only  
224 to improve the language and readability. After using this tool/service, the  
225 author reviewed and edited the content as needed and takes full responsibility  
226 for the content of the publication.

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