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Physics-Informed Machine Learning Digital Twin for 2 Thermal Turbulent Jet Temperature Prediction

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4

Abstract

5 *Keywords:*

6

1. Introduction

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2. Related Work

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

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

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

35 The transition from industrial applications to more sophisticated model-
36 ing approaches has been marked by significant developments in physics-based
37 digital twins. Component-based reduced-order models [21] have enhanced
38 system modeling capabilities, while the integration of machine learning with
39 physics-based modeling has shown promising results [22]. Advanced frame-
40 works combining neural networks with physics-based models [23] have im-
41 proved prediction accuracy, and physics-based digital twins have been suc-
42 cessfully implemented in predictive control systems [24]. These developments
43 have particularly benefited thermal and fluid systems, where physics-based
44 modeling is essential for accurate system representation [25, 26].

45 Building upon these physics-based foundations, fluid mechanics applica-
46 tions of digital twins have evolved to handle increasingly complex systems.
47 The simulation aspects of digital twins [27] provided a crucial framework for
48 fluid dynamics applications, which has been further refined through various
49 modeling approaches [28]. Machine learning-based digital twins for dynam-
50 ical systems [29] and physics-based compressive sensing [30] have enhanced
51 the capability to model complex fluid behaviors. Digital twin modeling tech-
52 niques have advanced significantly [31], incorporating both data-driven and
53 physics-based approaches [32]. These advancements have enabled more ac-
54 curate representation of complex flow phenomena [33], particularly beneficial
55 for turbulent jet applications.

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

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

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

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

86 3. TurbTwin: An AI-Driven Digital Twin Framework for Thermal 87 Turbulent Jet Simulation

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

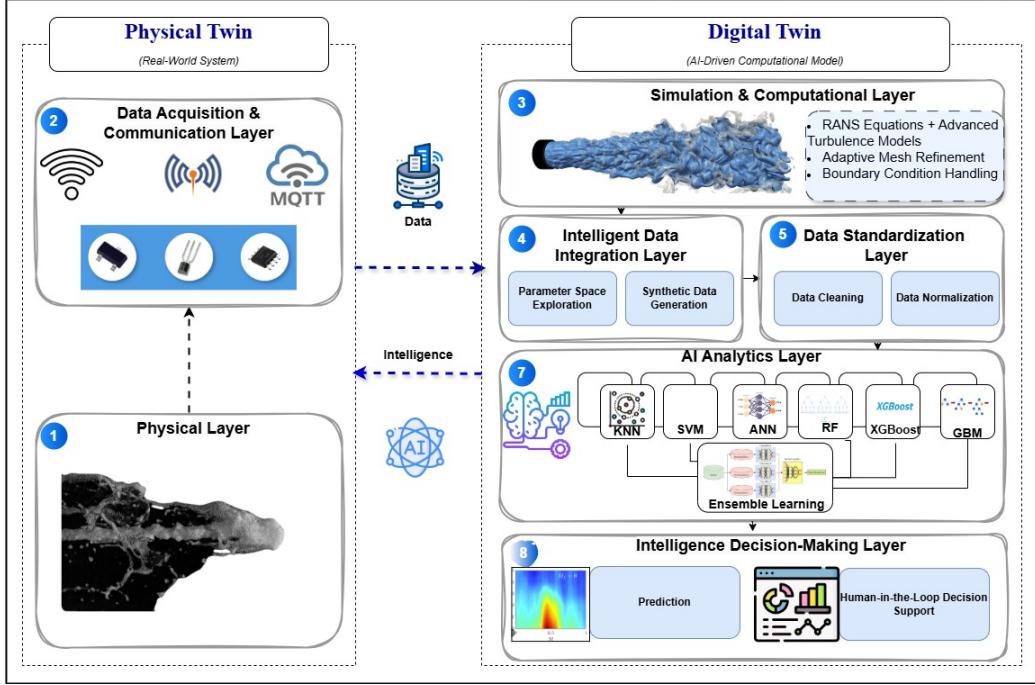


Figure 1: TurbTwin Architectural Framework

95 3.1. Framework Architecture Overview

96 3.1.1. Physical Twin (Real-World System)

97 The Physical Twin serves as the foundational entity for the integration of
98 99 cyber-physical systems, consisting of two distinct layers: the physical layer
 00 and the data acquisition and communication layer.

- 01 • **Physical layer:** represents the core components of the system, in-
 02 cluding the experimental setup designed to investigate turbulent jet
 03 dynamics. This layer includes a thermally insulated cylindrical tank
 04 equipped with various measurement instruments, such as K-type ther-
 05 mocouples for temperature monitoring and dedicated inlet and outlet
 06 pipes for controlling fluid flow. The physical layer provides the real-
 07 world environment for the experiments.

08 -]

- 09 • **Data acquisition and communication layer :** serves as a critical
 10 component that enables continuous monitoring, processing, and trans-
 11 mission 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-

146 flows for parameter variation studies, enabling a comprehensive under-
147 standing of the system's behavior across different operational scenarios.
148 This computational infrastructure emphasizes numerical efficiency, ac-
149 curacy, and systematic validation protocols to maintain high-fidelity
150 simulation results, bridging the gap between physical measurements
151 and predictive modeling.

152 • **Intelligent Data Integration Layer**

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

164 1. **Define Simulation Parameters**

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

168 2. **Run Automated Simulations**

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

172 3. **Activate Data Collection Pipelines**

173 Automatically extract relevant physical quantities, such as tem-
174 perature, velocity, and pressure, from the simulation results. These
175 data points are essential for further analysis and model training.

176 4. **Ensure Data Quality**

177 Implement automated quality assurance mechanisms that validate
178 the consistency, accuracy, and completeness of the collected data.
179 This ensures high-quality data throughout the data collection pro-
cess.

181 **5. Store Data in Structured Formats**

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

184 **6. Automate Data Labeling and Tracking**

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

- 189 • **Data Standardization Layer** The Data Standardization Layer is a
190 crucial preprocessing component in the digital twin architecture, en-
191 suring data consistency and compatibility for machine learning. It
192 involves three primary transformations: unscaled data preservation,
193 which maintains the original physical meaning of the data; standard-
194 ization, which establishes uniform statistical properties across datasets;
195 and normalization, which optimizes the data for improved algorithm
196 performance. Automated pipelines are employed to ensure consistent
197 data representation across various scales and units, allowing for seam-
198 less integration of data from physical sensors and numerical simulations.
199 This layer plays a key role in enhancing model training by preserving
200 data relationships while optimizing the effectiveness of machine learn-
201 ing models.

- 202 • **Predictive Analytics Layer**

- 203 • **Intelligence Decision-Making Layer**

204 3.3. *Ensemble Learning*

205 **4. Evaluation and Experimental Results**

206 This section provides an overview of the implementation and evaluation
207 process of the proposed framework. It covers the experimental setup, in-
208 cluding the tools and environment used, followed by a description of the
209 datasets and their preparation. Next, the experimental results are presented,
210 demonstrating the framework's performance. Finally, a comparative analy-
211 sis is conducted to benchmark the approach against state-of-the-art methods,
212 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 process:*

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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