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TESI DI LAUREA

# A Causal Digital Twin Framework for Sustainable Decision-Making in Smart Manufacturing Systems


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**Abstract**

Today's manufacturing systems are getting more complex because there is a strong need to use energy in a better way and to make smart and clear decisions. This thesis presents a new framework called the Causal Digital Twin Framework (CDTF), which helps make better and more sustainable decisions in smart factories. Unlike older Digital Twins, that mostly do simulations and monitoring, CDTF works with real-time data, connects physical and digital parts, uses AI to make predictions, and finds the real causes behind problems. This framework has four main layers: Data acquisition and Integration layer, Cyber Physical Synchronization Layer, AI-Driven Decision Making Layer, and Causal Inference and Modeling Layer. It was tested on a real 3D printer (Prusa i3 MK3S), where more than 9.6 million sensor data points were collected using MQTT, handled with Node RED, and saved in a TimescaleDB system. Also, live dashboards were made with Grafana to show predictions, problems, and cause-related insights in real time. Layer 1 is used to collect real time data from the physical system. Layer 2 connects the physical and virtual parts, making sure the data moves and works smoothly between them. In Layer 3, an XGBoost model was used to predict how long the printer parts will keep working ($R^2 = 0.8078$), and it gave accurate results. Layer 4 moved from just finding connections to understanding real causes, using specific questions, causal models, OLS regression, and "what if" tests with the DoWhy tool. To check if the results were reliable, tests like VIF, Durbin-Watson, and special error checks were used. The results show that the CDTF helps with both predicting when maintenance is needed and finding the real reasons behind energy use and system problems. By using AI and causal analysis in a clear and well-structured way, this research improves Digital Twin technology to make it more transparent, understandable, and focused on saving energy. This new framework also supports building smart systems that can work on their own, can be repeated in other places, and follow ethical and responsible decision-making.

**Thesis General Description**

The thesis titled "A Causal Digital Twin Framework for Sustainable Decision-Making in Smart Manufacturing Systems" addresses the growing need for intelligent, explainable, and energy-efficient solutions in modern manufacturing. With industries under increasing pressure to align with the United Nations Sustainable Development Goals (particularly affordable clean energy and climate action), this research develops a novel Causal Digital Twin Framework (CDTF) that enhances traditional Digital Twin (DT) approaches by embedding causal inference alongside real-time monitoring, prediction, and decision-making.

**MOTIVATION AND PROBLEM STATEMENT**

Existing Digital Twin frameworks have proven valuable in simulation, monitoring, and optimization. However, they often fall short in three critical areas:

- Causal reasoning – they detect correlations but fail to explain *why* problems occur.
- Energy sustainability – they optimize processes without fully addressing energy consumption and efficiency.
- Transparency and trust – they provide results without sufficient explainability or human-in-the-loop validation.

The thesis responds to these gaps by designing a multi-layered system that integrates real-time sensing, AI-driven predictions, causal analysis, and expert validation, aiming to make manufacturing systems not only smart but also sustainable, interpretable, and responsible.

## FRAMEWORK DESIGN – THE FOUR LAYERS

The Causal Digital Twin Framework (CDTF) is structured into four main layers, plus a supporting task for expert validation:

**Layer 1: Data Acquisition and Integration**

- Collects real-time sensor data using MQTT, Node-RED, and TimescaleDB.
- Over 9.6 million entries of temperature, power, and motion data were gathered.
- Containerized via Docker for scalability and reliability.

**Layer 2: Cyber-Physical Synchronization**

- Ensures smooth synchronization between the physical machine and its digital counterpart.
- Automatically detects anomalies (e.g., overheating) and sends real-time G-code corrective commands to the 3D printer.
- Provides closed-loop control and transparency in operations.

**Layer 3: AI-Driven Decision-Making**

- Implements XGBoost regression models to predict the Remaining Useful Life (RUL) of machine parts.
- Achieved strong performance ($R^2$ = 0.8078) and generated real-time alerts for preventive maintenance.
- Supports energy-efficient operations and continuous learning by incorporating user feedback.

**Layer 4: Causal Inference and Modeling**

- The core innovation of this thesis, moving beyond correlations to true causal reasoning.
- Developed Directed Acyclic Graphs (DAGs) for key causal questions (e.g., effect of ambient temperature on power usage, fan speed on hotend temperature, utilization on RUL).
- Applied OLS regression, DoWhy, and CausalNex for estimation, validation, and counterfactual analysis.
- Validated causal insights using residual diagnostics, VIF, Durbin-Watson tests, and HAC corrections.
- Produced interpretable “what-if” simulations to support transparent decision-making.

**Supporting Task: Expert Involvement and Validation** (conceptualized but not fully implemented)

- Designed to integrate human expertise into decision loops.
- Ensures AI and causal outputs align with practical, domain-specific knowledge.
- Bridges the gap between machine predictions and real-world manufacturing constraints.

## CASE STUDY – 3D PRINTER APPLICATION

The framework was tested on a Prusa i3 MK3S 3D printer as a real-world case study.

- Data from sensors (temperature, power consumption, movement) was continuously streamed and analyzed.
- A Grafana dashboard was built for visualization of live machine health, RUL predictions, and causal insights.
- Results confirmed that CDTF could:
  - ✓ Detect and correct physical-digital mismatches in real time.
  - ✓ Accurately predict component failures and schedule preventive maintenance.
  - ✓ Identify root causes of inefficiencies (e.g., ambient temperature significantly affecting energy use and print quality).
  - ✓ Support decision-making that balances energy efficiency, quality, and machine lifespan.

## RESULTS AND CONTRIBUTIONS

- Demonstrated that AI-driven predictions and causal reasoning can be combined into a single digital twin framework.
- Proved feasibility of real-time synchronization, fault detection, and energy optimization.
- Enhanced trust and transparency by explaining not only *what* happens but also *why*.
- Showed that CDTF is scalable, modular, and adaptable for broader industrial use.

## LIMITATIONS

- Focused primarily on energy consumption, without fully incorporating other sustainability metrics (e.g., carbon footprint, waste).
- Expert validation was conceptualized but not formally applied.
- Case study limited to a single machine (3D printer), requiring further scaling to industrial factory-level settings.
- Ethical considerations (privacy, accountability, bias in AI) were acknowledged but left for future work.

## FUTURE DIRECTIONS

- Extending the framework to cover carbon emissions, waste management, and circular economy metrics.
- Implementing the expert-in-the-loop process with structured workshops and feedback systems.
- Applying CDTF in larger, more complex manufacturing environments.
- Exploring reinforcement learning for adaptive, self-updating decision-making.
- Addressing ethical and legal aspects of AI in manufacturing.

## CONCLUSION

This thesis makes a significant contribution to the field of smart manufacturing and digital twins by proposing and validating the Causal Digital Twin Framework (CDTF). By combining real-time data acquisition, AI-based predictions, causal modeling, and human validation, the framework advances digital twin technology toward being more sustainable, explainable, and human-centered.

The CDTF not only predicts failures but also explains their causes, enabling evidence-based, energy-aware, and ethically responsible decisions. Although demonstrated on a 3D printer, its modularity and scalability make it a viable solution for broader industrial adoption, supporting the transition toward next-generation smart factories that are transparent, efficient, and sustainable.