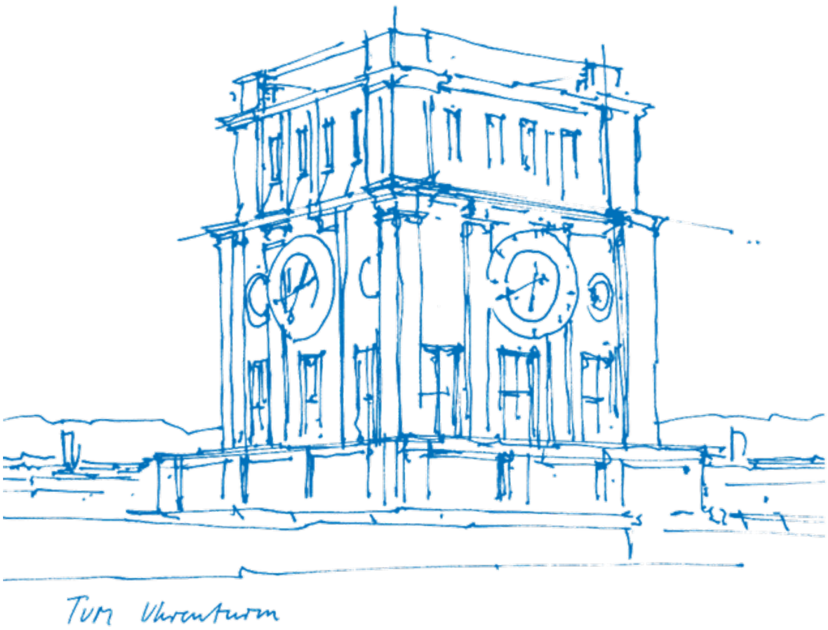
Chair of Information Systems and Business Process Management (i17)
Department of Computer Science
TUM School of Computation, Information and Technology
Technical University of Munich

Master's Thesis in Informatics

Nicolás Mario Arteaga García

Cotton Candy Digital Twin: Prescriptive Creation of Digital Twins



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Master of Science

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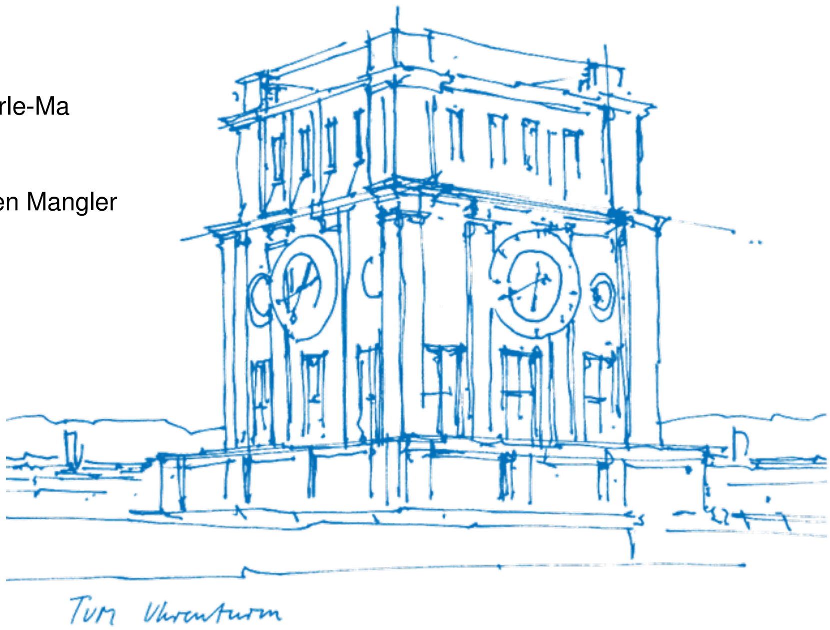

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Garching, 31.07.2025 Nicolás Mario Arteaga García

Abstract

150 - 180 words

Keywords: Digital Twin, Cotton Candy, BPTM, Data Collection, Data Science

Include three to five words, phrases, or acronyms as keywords.

Contents

List of Tables

List of Figures

Introduction

Motivation

As industries evolve, the ability to optimize processes while minimizing waste has become increasingly important. Digital twins (virtual representations of physical systems) are transforming how processes can be monitored, analyzed, and improved. While reactive digital twins respond to events as they occur, providing immediate yet limited feedback, predictive digital twins forecast potential outcomes based on historical and real-time data, enabling proactive adjustments. A more recent frontier is the prescriptive digital twin, which goes beyond prediction by recommending concrete actions to achieve goals such as improving efficiency, reducing energy consumption, or enhancing product quality.

This thesis explores the development of a prescriptive digital twin for the Cotton Candy Automata, a robotic system we designed at the Chair of Information Systems and Business Process Management from the TUM, to automate cotton candy production. The process provides a controlled and measurable environment in which to evaluate the capabilities of a digital twin, with key parameters such as heating time, temperature, process duration, sugar amount, and energy usage offering tangible performance indicators.

The construction of the digital twin follows a bottom-up approach. Instead of starting from abstract models or historical approximations, we relied on physical measurements and sensor data from the automata. Through repeated experiments, we empirically identified parameters that govern the system's behavior and integrated them into the digital twin. This allowed us to directly model the causal impact of system configurations on outcomes, such as energy consumption, production time, and product quality.

A central objective of this thesis is to compare the prescriptive digital twin to the simple baseline robotic system we created (the "unintelligent automata"). This comparison highlights the extent to which a data-driven, bottom-up digital twin can improve operational efficiency and decision-making. By analyzing metrics such as energy savings, time efficiency, and production quality, the research demonstrates the potential of prescriptive digital twins to contribute to more sustainable and effective industrial processes.

Research Questions

There are four research questions that we want to answer throughout this thesis.

(1) **How does the implementation of a digital twin improve production quality, time efficiency, and energy savings in the Cotton Candy Automata?** This question examines the extent to which the digital twin contributes to measurable performance gains. The analysis will compare key performance indicators of the digital twin against the baseline automata to quantify improvements in quality, time, and energy consumption.

(2) **What correlations and dependencies can be identified in the data collected from the Cotton Candy Automata, and how do they shape the process outcomes?** By analyzing sensor data, this question aims to uncover the strongest relationships between variables such as heating time, spinning duration, and sugar input, and their effect on production quality. The findings will also be compared with the initial hypotheses formed during empirical testing to validate or refine our understanding of the system.

(3) **To what extent can the prescriptive digital twin provide actionable recommendations to optimize cotton candy production, including variables beyond current experimental control?** This question assesses the digital twin's capacity to recommend process adjustments. In particular, it considers environmental factors such as ambient temperature and humidity, which cannot be directly manipulated in the present setup but are likely to be influential in real-world production scenarios.

(4) **How transferable and generalizable are the methods and insights derived from the Cotton Candy Automata digital twin to other process environments?** A digital twin is most valuable when its methods are not bound to a single technical context but can be applied across different domains. While the Cotton Candy Automata provides a controlled and measurable environment for testing, the broader relevance of this thesis depends on whether the bottom-up, sensor-driven methodology can extend to other processes.

Contribution

The contributions of this thesis are as follows:

- A literature review on the topic of Business Processes, Cotton Candy, and Digital Twins, situating this unusual case study within both technical and food-science domains.
- The development of a Cotton Candy Automata operated by a Universal Robots arm, providing a reproducible physical system for experimentation.
- The development of a Cotton Candy Digital Twin that controls, predicts, and prescribes to the Automata. This represents, to the best of our knowledge, the first attempt to model cotton candy production as a cyber-physical process, thereby extending digital twin principles into an entirely new domain.
- A documentation of the implementation of the System in its different versions, including the architecture of the systems and services as well as their communication protocols.
- A systematic documentation of the data collection process for cotton candy production, ensuring transparency and reproducibility.
- An analysis of the collected data using machine learning models, highlighting predictive features and demonstrating how quality outcomes can be linked to process parameters.
- A documentation of the creation of the Digital Twin model, showing how bottom-up data-driven modelling can capture even complex, sensor-rich processes such as when hot spun sugar starts to form cotton candy.
- An evaluation of the prescriptive Digital Twin implementation, demonstrating its ability not only to mirror and predict but also to recommend interventions in real time.

Methodology

To position this thesis within an established research tradition, we adopt the Design Science Research (DSR) paradigm as defined by Hevner et al. [1]. DSR is particularly well suited for this work, as it emphasizes the design and evaluation of innovative artefacts that address real-world problems while simultaneously contributing to scientific knowledge. In addition, we draw on the methodological principles of Zaki and Meira [2] for data collection, cleaning, mining, and analysis, which form the technical backbone of constructing a data-driven digital twin.

Design Science in Information Systems

DSR has emerged as a cornerstone methodology in the field of Information Systems. It acknowledges that research in this domain often involves the creation of artefacts such as models, methods, systems, and frameworks, which are then evaluated both for their practical utility and their theoretical contribution. According to Hevner et al., three cycles guide DSR: the *relevance cycle*, which connects the research to its practical environment; the *rigor cycle*, which ensures grounding in scientific theories and prior work; and the *design cycle*, which iteratively builds and evaluates artefacts.

The value of DSR lies in its dual orientation: it not only produces useful artefacts but also advances theoretical understanding by abstracting design knowledge from practical interventions. This methodological orientation is particularly fitting for this thesis, which aims to design and implement a prescriptive digital twin that is both technologically functional and theoretically informative.

Application to This Thesis

In the context of this thesis, the central artefact is the digital twin of the Cotton Candy Automata. The automata itself, a robotic system combining a universal robot arm with a customized cotton candy machine, serves as the physical environment in which the artefact is embedded. The digital twin comprises multiple layers:

- a **virtual representation** of the production process, constructed as a cpee process model.
- the **data infrastructure** as process logs required to capture and preprocess parameters such as temperatures, humidity, weights, energy consumption, and run times.
- the **analytics and prescriptive components** as machine learning models, that generate recommendations to optimize quality, time, and energy efficiency.

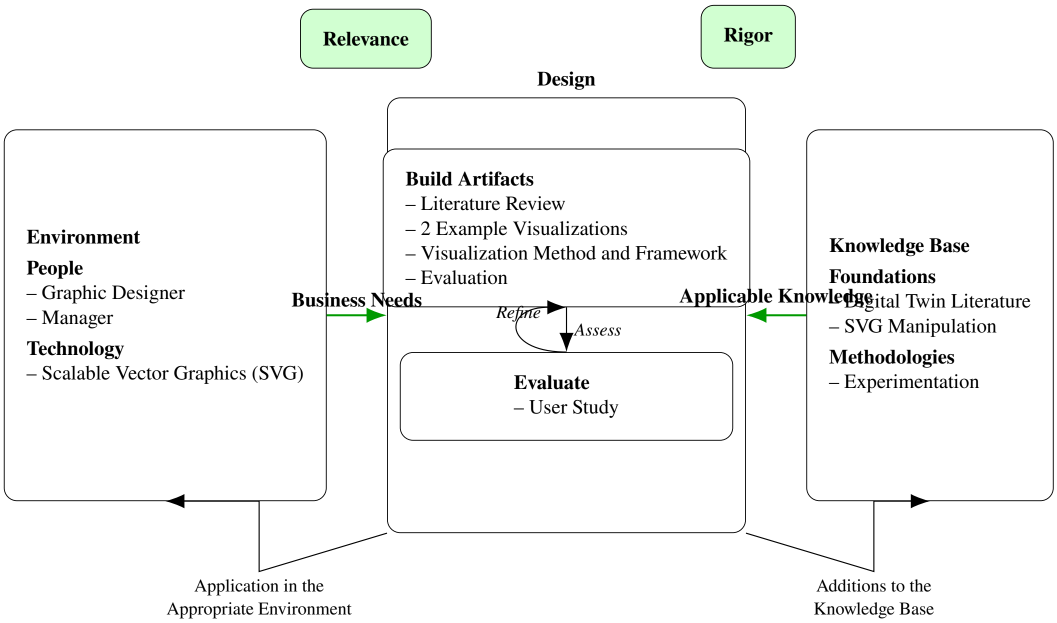
Stakeholders. The primary stakeholders in this research include (1) researchers in business process management and digital twin methodologies, who benefit from methodological contributions; (2) practitioners in food engineering and small-scale manufacturing, who may apply the findings in similar production settings; and (3) the developers of cyber-physical systems, who can draw on the design insights gained from building a bottom-up prescriptive twin.

Artefacts. Following Hevner's classification, the artefacts created in this thesis include:

1. a functioning **digital twin system** for cotton candy production,
2. a set of **process and data models** capturing the causal relationships between process parameters and product outcomes,

Figure 1

Design Science Research Framework (after Hevner et al., 2004; Hevner, 2007).



3. the **evaluation framework** comparing the digital twin to the baseline automata.

Research cycles. The relevance cycle is embodied in the real-world setting of cotton candy production, a domain where quality and stability are strongly affected by environmental and process parameters. The rigor cycle is ensured by grounding the work in prior digital twin research, food science on cotton candy physicochemical properties, and established process mining and machine learning techniques. The design cycle is realized through iterative development: building the digital twin prototype, evaluating it against baseline performance, and refining its prescriptive logic based on empirical evidence.

Data Collection and Analysis

Complementing the DSR framework, we adopt the methodological basis of Zaki and Meira [2] to structure the collection and analysis of process data. This involves four steps: (1) systematic collection of sensor data from the automata (e.g., temperature profiles, humidity, and machine runtime); (2) preprocessing and cleaning to handle noise, missing values, and synchronization across streams; (3) process mining and statistical analysis to uncover dependencies between parameters and outcomes; and (4) machine learning for predictive and prescriptive modeling. These steps ensure that the digital twin is empirically grounded and continuously updated with real-world measurements.

Evaluation

This chapter evaluates whether the prescriptive Digital Twin achieves the goals set out in the research questions. We adopt a controlled experimental design that compares (i) the baseline "unintelligent" automata with an early, hand-guessed function approximation, and (iii) the prescriptive Digital Twin. Across multiple sessions and varying ambient conditions, we produce repeated batches with matched sugar input while randomizing parameter orders to mitigate carry-over effects.

To make "good" cotton candy measurable, we define a quality score that combines (a) formation consistency, (b) size and weight, and (c) short-term pressure after production. The score is computed automatically from the process quality measurement services. In addition to quality, we record time-to-handover-product and energy-per-process.

The primary analysis quantifies improvements of the Digital Twin over both baselines along three dimensions: (1) *descriptive* fidelity (ability to reproduce observed process behavior), (2) *predictive* accuracy (forecast of outcomes under parameter choices), and (3) *prescriptive* benefit (actual gains in quality, time, and energy when following recommendations). We report effect sizes and confidence intervals for each metric, and summarize results with aggregate improvements per session.

ite

Robustness checks include: (i) cross-validation with held-out runs; (ii) sensitivity analyses where individual sensors or features are ablated to assess dependence; and (iii) a qualitative sanity check in which automated scores are compared to brief human inspection. Finally, we assess transferability by repeating a subset of runs under altered environmental conditions and by replaying logs through the twin to verify that recommendations remain consistent.

Success criteria are met if the Digital Twin (a) increases the composite quality score while (b) reducing either time-to-product or energy-per-batch (preferably both), and (c) maintains these gains under the robustness checks above. The detailed results are presented in Chapter **??** and discussed in Chapter **??**.

Structure

So, we have Related Work where we go into existing literature on digital twins, food papers about cotton candy and data science book to build a solid foundation for our research. Important because we will use it a lot for our Data Collection, searching correlations and building models. Next, we have our Solution Design, where we explain the stakeholders involved, and the artefacts we are creating. This section will detail how we are building and evaluating our digital twin. Afterwards the Implementation Chapter, where we describe the technical details of our digital twin, including the data collection process, the modeling techniques used, and the integration with the physical cotton candy machine. Then Evaluation, where we assess the effectiveness of our digital twin in optimizing the cotton candy production process, based on the research questions outlined earlier. Afterwards in Discussion, we reflect on the implications of our findings, we answer the the limitations of our approach, and potential avenues for future research. And finally Conclusion, where we summarize the key contributions of our work, and its significance in the broader context of digital twin research and applications.

Rewrite this after you finished

Rewrite this after you finished

Related Work

This chapter reviews related work that informs the development of a prescriptive, data-driven digital twin for the Cotton Candy Automata. The discussion is structured around three areas: (1) the conceptual foundations of digital twins, (2) the results and discussion of our literature search on digital twins, and (3) the physicochemical background of cotton candy. To ensure transparency, we include the full literature search procedure and selection results.

Conceptual Foundations of Digital Twins

VanDerHorn and Mahadevan [3] reviewed more than forty definitions of digital twins and proposed a consolidated characterization distinguishing them from digital models and digital shadows. Their work highlights the essential elements of a DT: a physical system, a virtual representation, and continuous data exchange between the two. While this definition provides conceptual clarity, it leaves open the question of how to realize DTs in practice, particularly in small-scale or experimental domains.

Perno et al. [4] addressed implementation challenges in the process industry. They identified barriers such as interoperability, sensor reliability, and data quality, as well as organizational enablers like management support and standardization. These insights underscore the practical difficulties of creating robust DTs but do not provide concrete examples of small-scale implementations. In contrast, our thesis contributes an empirical case where sensor reliability and data quality are directly confronted in a novel food-production setting.

Kreuzer et al. [5] performed a systematic literature review on artificial intelligence in DTs and found that most works neglect real-time data, bidirectional feedback, and explainability. These gaps motivate the approach in this thesis, which builds a bottom-up DT explicitly designed to integrate real-time sensor data and prescriptive feedback loops.

Literature Search for Digital Twins

To identify digital twin methods relevant to business processes and prescriptive capabilities, we conducted a structured search on Google Scholar using the operator `allintitle`. The search and filtering followed a three-step procedure applied to both the digital twin and cotton candy queries:

- **Step 1 (S1) – Title Screening:** Titles were inspected to exclude papers clearly out of scope (e.g., purely visualization-oriented, domain-specific without transferable methods, or not addressing digital twins at all).
- **Step 2 (S2) – De-duplication and Access Check:** Duplicates were removed, and inaccessible papers were excluded.
- **Step 3 (S3) – Abstract Skim:** Abstracts (and figures where available) were skimmed to exclude purely theoretical works without models, examples, or process-level analysis.

Most results were excluded for focusing solely on visualization, lacking process-level applicability, or remaining purely conceptual. The complete results are shown in Table **??**, with only four papers retained as directly relevant.

Discussion of Relevant Works

The following four papers were retained after the selection process:

- **Fornari et al. [6]**: The "Digital Twins of Business Processes" manifesto provides a research agenda, highlighting challenges such as model-execution alignment, integration of runtime data, and prescriptive capabilities. Our thesis differs by operationalizing these ideas in practice, demonstrating a real-time prescriptive DT in a robotic food production process.

Table 1
Literature search results for Digital Twin (allintitle).

Search Term	Results	S1	S2	S3	Rel.
"digital twin" "business process"	14	4	3	3	
"digital twins" "business processes"	6	1	1	1	[6]
"business process digital twin"	2	1	0		
"digital twin" "business process" "implementation"	1	1	0		
"digital twin" "business process" "framework"	0				
"digital twin" "business process management"	1	0			
"digital twin" "process industry"	17	0			
"digital twin" "feedback loop"	1	0			
"digital twin" "candy"	0				
"digital twin" "cotton candy"	0				
"digital twin" "process mining"	13	3	3	1	[7]
"digital shadow" "business process"	0				
"digital twin" "data-driven" "process"	13	1	1	1	[8]
"digital twin" "prescriptive"	11	3	3	1	[9]
"digital twin" "bidirectional"	8	2	1	0	
"digital twin" "real-time control"	17	0			
"digital twin" "artificial intelligence" "literature review"	3	3	3	1	
"digital twin" "artificial intelligence" "model"	10	1	1	0	
"digital twin" "explainable ai"	12	1	1	0	
"digital twin" "machine learning" "prescriptive"	0				
Sum	**129**	**21**	**17**	**8**	**4**

Selection Steps: S1 = title screening, S2 = duplicate removal and access check, S3 = abstract skim. The **Sum** row reports the number of articles remaining after each step.

- **Vitale et al. [7]**: This work combines process mining and DTs for anomaly detection in water distribution networks. While methodologically similar in its bottom-up data use, it focuses on large-scale industrial infrastructure. In contrast, we apply the approach to small-batch food production, showing the generalizability of process mining concepts to new domains.
- **Walton et al. [9]**: Proposes a unified DT architecture integrating physical, virtual, and prescriptive components. Unlike this framework-level contribution, our thesis demonstrates a physical implementation where prescriptive recommendations directly optimize process outcomes.
- **Stojanovic and Milenovic [8]**: Among the first to propose explicitly data-driven DTs, focusing on big data clustering for laser cutting optimization. Their approach is unsupervised and anomaly-oriented. Our work advances this by implementing a supervised, sensor-driven, and prescriptive DT in a food context.

These works highlight both the potential and the limitations of current digital twin research. In particular, they motivate Research Question 3 (see Section **??**), which asks whether a prescriptive DT can provide actionable recommendations in a small-batch food production setting.

An Alternative Approach

Some works excluded at Step 3 still highlight important alternative perspectives. For example, Giussani et al. [10] embed a Digital Twin of the Organization into BPMN (Business Process Model and Notation: a standard notation for modeling business processes) processes to enable pre-implementation simulation and runtime adaptation. This model-driven, top-down orientation contrasts with our bottom-up, sensor-driven approach, reinforcing the novelty of applying empirical, data-driven methods to DT development.

Physicochemical Background of Cotton Candy

Although digital twins have not yet been applied to cotton candy production, existing food science research provides an essential foundation for interpreting process data. To identify relevant studies, we conducted a targeted literature search using the same three-step procedure as in the digital twin review, but with the operator `intitle` due to the limited number of publications on cotton candy. The results of this search are summarized in Table **??**. Labuza [11] demonstrated how temperature and relative humidity trigger glass transition and recrystallization, which ultimately determine collapse and stability. Terashima [12] extended this work using differential scanning calorimetry, analyzing how cooking conditions influence crystalline and amorphous states of spun sugar. Together, these studies underline why humidity and temperature are critical factors: they directly affect the durability and quality of the spun product.

Building on these insights, our thesis integrates physicochemical knowledge into the design of the digital twin. The findings informed both our interpretation of humidity and temperature sensor data and the way we translated thresholds into predictors of collapse and quality outcomes. This connection between physicochemical mechanisms and process behavior directly motivates Research Question 2 (see Section **??**), which examines how correlations between variables such as humidity, temperature, and production quality can be identified and modeled in the cotton candy process.

Table 2

Literature search results for Cotton Candy Physicochemical Background (`intitle`).

Search Term	Results	S1	S2	S3	Rel.
"cotton candy" "humidity"	5	3	2	2	[11], [12]
"cotton candy" "temperature"	25	3	1	0	
"cotton candy" "crystallization"	9	2	0		
"cotton candy" "stability"	12	2	0		
"cotton candy" "quality"	16	2	0		
"cotton candy" "food engineering"	1	1	0		
Sum	**68**	**13**	**3**	**2**	**2**

Selection Steps: S1 = title screening, S2 = duplicate removal and access check, S3 = abstract skim. The **Sum** row reports the number of articles remaining after each step.

Synthesis

The reviewed literature reveals three clear gaps. First, conceptual clarity exists, but practical small-scale DT implementations remain rare. Second, prescriptive DTs are proposed architecturally but seldom realized in practice. Third, food science research on cotton candy explains physicochemical behavior but does not connect to data-driven optimization. By integrating these threads, this thesis contributes a prescriptive, bottom-up digital twin that combines sensor data, process mining, and food science insights to optimize a tangible robotic production process.

Solution Design

• What is the physical structure of cotton candy? What aspects define "quality" of cotton candy? • What are the key factors that affect quality? • How does it change with production parameters? What we already learned doing cc is -> The notes from the notion

Design Goals and Approach

System Architecture

Sensor Design and Placement

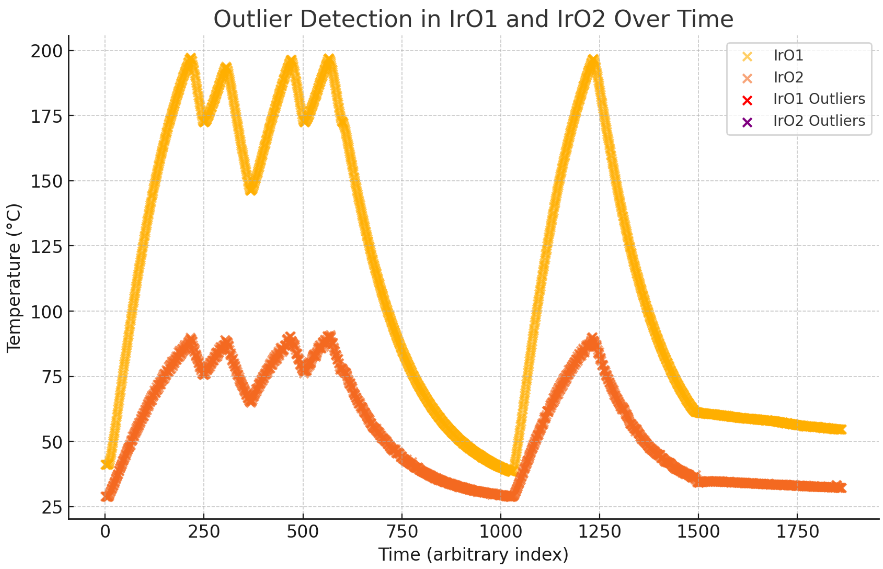
Temperature Sensors

Infrared Object Temperature Sensor To monitor the thermal behavior of the cotton candy machine's rotating head, we use a non-contact infrared temperature sensor (MLX90614). This sensor is well suited for the application due to its high accuracy (±0.5°C in the critical 0–50°C range) and wide measurement span, covering object temperatures from –70°C up to 380°C. These properties make it ideal for tracking the heating phase where the sugar melts and begins to form cotton candy.

Although only one sensor is used during regular operation, we conducted a dedicated experiment using a second sensor to evaluate placement and correlation. One sensor was positioned inside the machine, 3cm above the rotating head, while the other was mounted below the machine base, pointing sideways toward the head at the same distance. Over 2000 seconds, both sensors recorded temperature data to assess the relationship between internal and external readings.

Figure 2

Comparison of internal (IrO1) and external (IrO2) infrared temperature sensors over 2000 seconds.



A linear regression analysis showed a strong correlation between the two sensors, with a coefficient of determination $R^2 = 0.996$, slope $a = 0.383$, and intercept $b = 12.15$. The resulting model for estimating the external temperature T_{outside} based on the internal reading T_{inside} is:

$$T_{\text{outside}} = 0.383 \cdot T_{\text{inside}} + 12.15$$

This strong correlation implies that the internal head temperature can be reliably estimated from the external measurement. Consequently, the system design employs only a single infrared temperature sensor mounted outside the head during operation. This placement avoids obstructing the cotton candy formation process while maintaining accurate and reliable thermal monitoring. The sensor's communication protocol and technical specifications are described in the official documentation [13].

Humidity Sensors

Humidity Sensor Offset

During idle phases, the inside humidity sensor consistently showed 2–5% higher values than the outside reference. This effect is best explained by placement and airflow, since it disappeared once the machine was running. Replacing the sensors produced the same pattern, confirming it is not sensor wear but an environmental effect. For the digital twin, this means that differences observed during operation can be interpreted as true process dynamics, such as moisture accumulation, rather than calibration bias.

Energy Monitoring

Cotton Candy Product Characteristics

What we learned empirically doing CC

- write times, forms, radius why that radius etc etc etc => We can create a formula of how we think it behaves, that we can compare afterwards in the Data Recollection Evaluation.

Physical Structure

Quality Indicators

Excluded Factors

Process Parameters and Environmental Factors

Humidity

Temperature

Spinning Speed

Sugar Amount and Formulation

Prescriptive Digital Twin Design

- **What is the physical structure of cotton candy?**

Cotton candy is primarily composed of spun sucrose, which can exist in two main forms:WHat we saw in the paper. . .

What aspects?

YES: Volume density -> How much sugar is in a given volume -> Weighing sample and measuring volume (water displacement) => Doing this wiht a trichter that has the exact volume written. How does it change wiht more or less humidity?

NO: Visual appearance -> Fiber structure, color, consistency -> Visual inspection, photography + image analysis (even with your phone and Python/OpenCV) => we are not gonna do this because we learned that it is not really possible to distinguish the fibers with the naked eye. Its a full master thesis on its own

NO: Texture & mouthfeel -> Stickiness, softness, “melt-in-mouth” -> Manual touch test, break force => Stickiness is interesting to measure but probably difficult more on it later NO: Hygroscopic behavior -> Stickiness as it absorbs moisture -> Weighing sample over time at room humidity => This is very interesting, takes time to measure but hey -> NO BC WE WILL CREATE THEM IN DIFF ENVIRONMENTS AND CANNOT CREATE A CONTROL CAPSULE

YES: Crispness vs softness -> Related to crystallinity -> Compression test (kitchen scale or small force sensor) => It would mean measureing how much compression force is needed to break the fibers, very difficult, we build a model that we could test between CC and after measuring volume we weighted it, we tested this and that and concluded. . .

B. Compression Test • Use a small kitchen scale or force sensor. • Press gently until collapse starts. • Record maximum weight/force applied. • Amorphous cotton candy tends to be softer; more crystalline samples resist compression.

NO: Structural stability -> How long it holds shape over time -> Timed visual check at room conditions => Takes long to test,

NO: Taste (subjective) -> Flavor preception is too subjective so we will not do this, but it is important to note that it is a factor in quality perception.

• How does it change with production parameters?

How can we change the environment and control so that production parameters are changed • Humidity: Higher humidity leads to more stickiness and faster recrystallization. -> How to simulate Humidity? The gas environment during spinning directly changes how much of the sucrose becomes crystalline vs amorphous. • More oxygen & moisture → more crystallization. • Less oxygen & low moisture (like nitrogen or dry air) → more amorphous content. -> We cannot change the environment, but we can change the humidity of the process with: - Airflow / fans -> Stronger air movement near spinner -> Helps dry fibers during flight/creation, reduces moisture pickup. -> YESSSS LETS DO THIS

Affect on more humidity durign spinning -> Fibers may break sooner, become shorter, thicker. fibers stick together more. and after spinning -> Fibers collapse and shrink, Loss of volume (shrinkage), stickiness increases. what about compression? Immediately after spinning (fresh) - Fibers in humid air are thicker, stickier → denser structure → higher compression resistance initially (less fluffy, more "compact"). - Less air trapped between fibers → more force needed to compress. Shortly after spinning (as moisture is absorbed) - As fibers absorb moisture, they soften → compression force quickly drops. - Structure collapses under small loads.

Compression is kind of complicated to test since: Actually, at high humidity: • At first → more compact = higher compression resistance. • But as time passes → absorbs moisture → weaker structure = lower compression resistance.

In contrast, at low humidity: • The fibers stay dry, fluffy, and light. • Lower compression resistance but much better structural stability over time.

Humidity Level Result that we think we could achieve: Low RH < 30% Light, fluffy, large volume, fine fibers. High RH > 60% Denser, smaller volume, coarser fibers, faster shrinkage.

• Temperature: Higher temperatures can lead to more amorphous structure, but too high can cause burning. We have no control over this, as we are gonna see in the Solution Design, we are using a machine that always stays at the same ratio of temperature when at work. -> What we can control and change is the Cooking time, so the temperature that the head had when inserting the suagr and the time that we let the cotton candy get created, and let the arm roll. -> What this hopefully gives us is the change in structure that we can test with the compression test and a bigger volume.

• Spinning speed: Faster spinning may lead to finer fibers, affecting texture. Spinning speed (Higher RPM) Creates finer fibers, helps counteract thickening effect of humidity. -> We cannot control this. The given machine always spins in the same speed.

- One big variable that I had at the start was the Sugar amount. Thinking naively, I thought that more sugar would lead to more volume, but this is not the case. The amount of sugar in the process is always the same, and we are not changing it. We are always using the same amount of sugar for each production, which is 10 grams. -> Adding more won't help volume, might increase stickiness. And we are not measuring this change in stickiness as we saw before.

- Sugar formulation -> Use anti-hygroscopic additives (e.g., small % of maltodextrin or stabilizers) -> Slows moisture absorption. Often used in industrial production. We are not chanign the sugar formulation. We are always using the same sugar from the supermarket for making it easier to reproduce the results.

Prescriptive Digital Twin Flow

- We have an Environment that we cannot control, but we can measure it. - We have a process that we can control, but what exactly? THe time of cook? (Yes) The amunt of sugar? (Yes, but doesnt impact), The heating up before spinning? (Yes, but only energy savings impact) The . . . - We have a product that we can measure and evaluate the quality, but how? (First measure the Volume and then the compression stress, etc)

With 200 points of this data we can create a Model that can forecast the quality mark of the product looking at the ENV and the Process Rules. With Desicion Trees since this and that. . .

With the Forecasting we can change the Process rules to imporve the quality of the product. How? With Decision Trees? Trasvering back? How should it be done? I dont know yet.

Figure 3
My Figure Caption

A note describing the figure

Thermal Study on Cotton Candy

Cotton candy consists of spun sucrose that cools rapidly, forming a mostly amorphous structure — but: • Over time, this amorphous state can convert into crystalline form. • The ratio between crystalline and amorphous sucrose affects: • Texture • Stability • Taste • Shelf-life

This paper provides very solid experimental data on how production parameters influence the physical structure (crystalline vs amorphous) of cotton candy.

Crystalline is . . . Amorphous is . . .

Knowing how production parameters (like gas environment) affect structure can inform optimal production recipes. We are not gonna compare CCA vs CCN, since we are always using Normal Air but We learn about the importance of humidity, and want to use it for our Data Recollection since this is important For the Prescriptive twin design.

This helps with us taking the decision how to measure the quality of CC when doing data recollection and giving a note to the process.

What makes it difficult is that the changes are fine and little, and we dont really know if we are gonna be able to distinguish them, but we did research and will introducte this in the Solution Design.

Implementation

Starting Automata v0

TODO What we learned when we created the automata and the simple function that we are gonna use for data collection.

Its Parameters/Features

Sugar Amount

To calibrate the sugar dispensing system, we measured the mass of sugar released over dispensing durations of 0.5s, 1s, 1.5s and 2s, with ten trials conducted at each setting (noting that 2 s slightly overflowed the spoon). The resulting median amounts dispensed were 8.50g, 12.63g, and 16.64g, 20.58g, respectively. These findings confirmed a roughly linear relationship between dispensing duration and sugar quantity. For all subsequent trials and modeling, we standardized the input to 1s of sugar dispensing (12.63g).

Waiting Time

Waiting time refers to how long the robot arm has to wait until sugar starts coming out of the head. The cold-start time was a variable used for the first time (102s) with an environment temperature of 25°C.

In the digital twin implementation, this parameter is not required, as the model incorporates the actual spinner temperature to predict flow onset directly. Variability in waiting time, primarily influenced by the preheating state of the spinner, is analyzed in the final section of this thesis.

Cooking Time

The default cooking time is 105s. This starts once the sugar starts flowing out of the spinner. probably becauase the spinner has reached the desired temperature for more than (10-20 seconds). (TODO: Be sure about this) The spinning time is always 3.75s. 105/3.75 = 28 spins per run.

Cooldown Time

The cooldown time refers to the period during which the spinner runs without heating in order to cool down after the production run. This step prevents the sugar from burning in subsequent runs. A default cooldown time of 60s was applied. However, we are gonna investigate the effect of increasing or decreasing this value on product quality. The machine manual recommends a cooldown time of 120 s. We adopted the shorter interval of 60 s because, in practice, the operational cycle of refilling sugar and restarting the machine often extends the total interval to approximately 120 s.

Cotton Candy Maintenance Iteration

We record the number of cotton candy production iterations completed since the last maintenance of the machine. Preliminary observations indicate that extended operation without maintenance has a noticeable impact on product quality. The objective is to determine the optimal number of iterations that can be performed before maintenance is required. In this study, we begin with a maximum of 60 iterations. Maintenance involves removing residual sugar and unclogging the spinner using water.

Automata v1 and automatic Quality Score Implementation

We need the parameters for the quality score

Automatic Quality Score

Time-Efficiency

Energy Consumption Measurement

Energy consumption is recorded for each production cycle to enable optimization of process parameters for energy efficiency. These measurements, combined with quality metrics, allow the digital twin system to identify optimal parameter settings that minimize energy usage while preserving product quality.

Data Acquisition and Calculation

Power consumption is measured using a smart plug at 2-second intervals throughout the production process. Total energy consumption is calculated using trapezoidal integration of discrete power measurements:

$$E = \sum_{i=1}^{n} \frac{P_{i-1} + P_i}{2} \cdot \Delta t_i$$

where P_i is the power measurement at time t_i and Δt_i is the time interval between measurements. The resulting value is converted from Watt-seconds to Watt-hours for practical interpretation of the 5-minute production cycles.

This methodology accounts for energy consumption across all production phases (startup, heating, spinning, and cooldown) and provides the optimization target for energy-efficient cotton candy production.

Weight Measurement

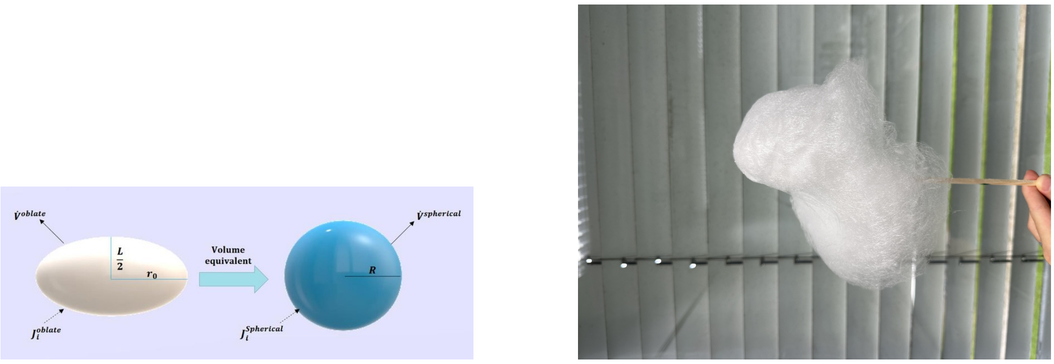
The input mass of sugar for each production run was manually measured using a precision scale with a readability of 0.01 grams. To determine the output mass of the produced cotton candy, the final product (including the stick) was weighed immediately after production using the same scale. The net weight of the cotton candy was then computed by subtracting the known weight of the stick, which was measured prior to the experiment and kept constant across all runs.

Accurate weight measurement was essential for evaluating the amount of produced cotton candy and for computing derived metrics such as the quality and Fluffiness Index. All weight measurements were recorded in grams with a precision of two decimal places.

Volume Estimation

To approximate the spatial characteristics of the cotton candy output, the product was modeled as an oblate spheroid — a flattened ellipsoid shape that approximates the typical morphology observed during production.

Figure 4
Comparison between geometric approximation and real cotton candy morphology



(a) *Idealized oblate spheroid*

(b) *Actual cotton candy output*

Measurements of the maximum width and height were taken manually using a standard ruler immediately after each production run. Based on these dimensions, the volume V was estimated using the standard formula for an oblate spheroid:

$$V = \frac{4}{3}\pi a^2 c$$

where a is the equatorial radius (half of the width) and c is the polar radius (half of the height). Although this approach does not capture fine-grained structural variations, it offers a practical and repeatable method to compare volumetric differences across runs.

To further assess structural quality, a Fluffiness Index was derived as:

$$\text{Fluffiness Index} = \frac{V}{\text{Weight}}$$

This index serves as a proxy for the density of the cotton candy, with higher values indicating a lighter, airier structure. The same procedure and tools were applied consistently across all production runs to ensure internal comparability.

Limitations in Volume Measurement

The estimation of cotton candy volume relied on manual measurements of width and height, followed by geometric approximation. While this method provides a reasonable basis for comparative analysis, it is subject to several limitations: (a) the inherently irregular and fragile structure of cotton candy, (b) potential observer bias during manual measurement, and (c) the assumption of a regular geometric shape. As such, the absolute values of estimated volume should be interpreted with caution. However, because the same procedure was applied uniformly across all experimental runs, the relative differences and trends derived from this method remain valid for assessing the effects of the digital twin optimization.

Data Collection & Analysis

Cite a little table showing the data we extracted from a process -> then the features and target we are building, etc...

Automata v2

From what we learned in the Data Analysis from before. We stop looking it as cooldown_time, ... etc and start looking at the temp of IRO as the top indicator/Changer to improve quality. We tweak the implementation, fragment more the bpm so that the process can cool itself down before starting, because of the importancy and correlation of cooldown_temp / start_temp

The new process looks like this BPM Process

Data Collection, Data Cleaning of the old logs & Analysis

Creation of our Temp Values Model

Did we use RandomForest or Decision Tree or Regression?

Automata v3 Our first Digital Twin

What is different in the implementation? Basically now we have a service with a model. In the next chapter we are gonna evaluate this final version with the v0 automata.

Prescription Part (No time)

Pressure Functions

Here I want to briefly show the pressure funcs we get from the scale and our implemented function, and why we decided not to use them (spoiler: To little time)

Product Quality Measurement

The development of an automated quality assessment system for cotton candy production presented significant challenges due to the inherently complex and variable nature of the product. Initial attempts to quantify cotton candy quality through traditional volumetric measurements proved unfeasible, as the product's form changes dramatically during the spinning process, making consistent volume measurements impractical within our laboratory constraints.

Quality Assessment Approach

Given the limitations of direct physical measurements, we established a ground-truth quality scoring system based on manual evaluation of the first 100 cotton candy samples. Each sample was assessed across three primary dimensions:

- **Weight consistency**: Deviation from target weight parameters
- **Structural integrity**: Evaluation of cotton candy fluffiness and density
- **Overall form quality**: Categorical assessment (1-3 scale: poor, acceptable, good)

The manual scoring process was conducted systematically to minimize evaluator bias, with scores ranging from 0 to 75 points. This approach provided a consistent baseline for developing an automated quality prediction system.

Algorithmic Quality Prediction

To automate quality assessment, we used machine learning to predict quality scores from sensor measurements. The system uses three types of input data:

- `touch_pos1-3`: Contact positions when the robotic arm touches the cotton candy to measure its size at different heights
- `max_pos1-3`: Pressure readings when moving the cotton candy down 5cm and back up, indicating structural strength

- `cc_weight`: Final weight of cotton candy (without stick) from 12.65g sugar input

We developed a linear regression model with custom features based on our understanding of cotton candy quality. This process involved several key steps and discoveries:

Understanding the Data: Each cotton candy sample gives us seven measurements - three touch positions, three pressure readings, and one weight. The touch positions tell us how big the cotton candy is at different heights. When the robotic arm can touch the cotton candy close to the stick, it means the cotton candy is fluffy and well-formed. When it has to reach far out, the cotton candy is either too dense or poorly shaped.

Smart Features: We created mathematical formulas that capture what makes good cotton candy. Instead of just using raw measurements, we built features that understand cotton candy physics:

- **Weight optimality:** We learned that 9–12 grams is the sweet spot for high-quality cotton candy. Too light means not enough sugar stuck to form proper structure, while too heavy indicates the presence of lumps from previous production runs, which creates an undesirable texture. Weights of 7–9 grams produce normal quality but receive lower scores, while anything below 7 grams indicates poor cotton candy formation.
- **Touch quality:** The touch position measurements work inversely—smaller distances (closer to the stick) indicate better structure and fluffiness. When the sensor reads 11, it means the robotic arm didn't make contact at all, representing the worst possible structure. The optimal range appears to be between 3–6, though the exact sweet spot within this range required empirical determination through our dataset. For the height (`touch_pos2`), 6 means no contact at all.
- **Pressure patterns:** The way cotton candy resists being pushed down reveals its internal structure. Too little pressure (below 20 grams) indicates the cotton candy is overly fluffy with poor cohesion, while too much pressure (above 30 grams) suggests crystallization and density issues that reduce quality. The optimal pressure range of 20–30 grams indicates proper sugar fiber formation and structural integrity.

the research that we
up that proves this

The First Problem - Training Bias: Our initial approach had a major flaw. We only used data from successful production runs (iterations 56 and above) because we thought this would give us a "clean" dataset. This was a mistake. The algorithm learned to recognize good cotton candy but had never seen truly bad cotton candy during training. When we tested it on early production attempts, it consistently gave scores that were 30 points too high - it simply didn't know what failure looked like.

The Solution - Complete Dataset Training: We retrained the model using all 72 samples, including the early failed attempts where we were still learning how to operate the machine. This gave the algorithm experience with the full quality spectrum, from complete failures to perfect cotton candy. The improvement was dramatic - the bias problem disappeared.

Why We Used All Data: Unlike typical machine learning projects where you split data into training and testing sets, we used our complete dataset for training. This decision follows best practices for small dataset scenarios [2]. Since our goal was to build a production tool rather than prove the algorithm works on unseen machines, using all available data gave us the best possible model for our specific setup.

Feature Selection Process: We systematically tested which measurements actually helped predict quality. Some obvious candidates failed completely - for example, height measurements were inconsistent because cotton candy changes shape so easily. We kept only the features that showed reliable correlation with human quality judgments across all our samples.

Validation Results

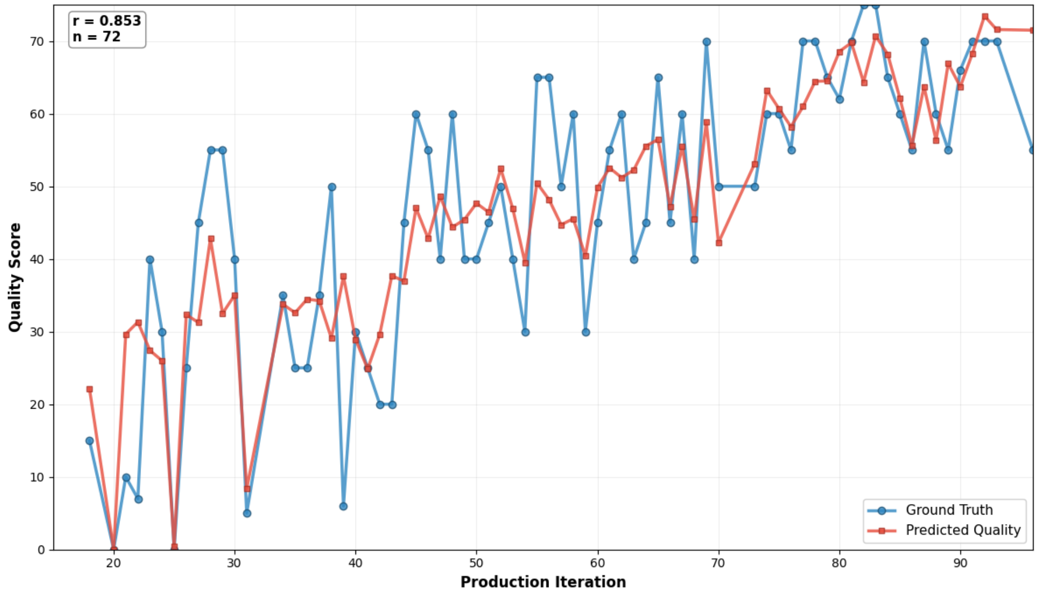
The final algorithm achieved strong correlation with manual assessments (r = 0.853, MAE = 7.83 points). The correlation coefficient shows the algorithm captures about 73

Figure **??** shows the close match between predicted and actual quality scores across all production runs, validating our approach for automated quality control.

The algorithm successfully captures both the learning progression evident in early iterations and the quality consistency achieved in later production runs, providing a reliable foundation for automated quality control in the digital twin system. This automated quality assessment eliminates the need for manual evaluation while maintaining assessment accuracy, enabling real-time quality monitoring and process optimization.

Figure 5

Comparison of manual quality scores (ground truth) and algorithmic predictions across production iterations. The strong correlation (r = 0.853) validates the automated quality assessment approach.



Feature Engineering for Decision Tree Optimization

To enable effective machine learning optimization, the raw process data was transformed into a structured feature vector suitable for decision tree modeling. This preprocessing involved careful selection and organization of variables to maximize predictive power while minimizing redundancy and computational complexity.

Feature Vector Structure

The final feature vector consists of 28 carefully selected features organized in a logical hierarchy:

1. **Process Parameters (6 features):** Core decision variables including iteration since maintenance, wait time, cook time, cooldown time, and derived timing metrics (duration until handover and total duration)
2. **Environmental Baseline (2 features):** External humidity and temperature captured at process initiation to establish ambient conditions
3. **Internal Environmental Dynamics (20 features):** Four internal sensors measured across five critical process phases:
   - Internal humidity (InH) and temperature (InT) sensors
   - Infrared ambient temperature (IrA) at the sensor location

Redundancy Elimination Strategy

Analysis of environmental sensor data revealed significant redundancy in external measurements, where external humidity and temperature remained virtually constant throughout the production process (±0.4% and ±0.1°C variation respectively). To optimize the feature set:

- **External sensors** were reduced from 10 measurements (2 sensors × 5 phases) to 2 baseline measurements, capturing ambient conditions without repetitive data
- **Internal sensors** were retained across all 5 phases, as they exhibited substantial variation (internal humidity: -27% change, internal temperature: +15°C change, infrared ambient temperature and machine head object temperature: up to +58 units variation)

This optimization reduced the environmental feature space from 30 to 22 features while preserving all meaningful environmental dynamics, resulting in a 22% reduction in feature dimensionality without information loss.

Process Phase Identification

Five critical process phases were identified for environmental monitoring:

1. **Before turn-on:** Baseline internal conditions prior to machine activation
2. **After flow start:** Environmental state during active cotton candy production
3. **After flow end:** Conditions immediately following production completion
4. **After weigh start:** Environmental state at cooling phase initiation
5. **End:** Final environmental conditions post-cooling

This temporal sampling strategy captures the complete thermal and humidity evolution during cotton candy production, enabling the decision tree to learn correlations between environmental conditions and process outcomes.

Parameter Optimization Results

Through comprehensive analysis of the collected dataset using machine learning techniques (Random Forest, Extra Trees, and Gradient Boosting), we identified optimal parameter bounds for the three critical control variables. The analysis revealed that environmental humidity sensors (particularly `before_turn_on_env_InH` and during `flow_env_InH`) are the most important quality predictors, followed by timing parameters.

Optimized Parameter Bounds

Based on the decision tree analysis of high-quality samples (quality score ≥ 70), the following parameter bounds were established:

- **Wait Time:** 34–54 seconds (optimal: 44 seconds)
  - Significantly reduced from initial default of 102 seconds
  - Reduces energy consumption while maintaining quality
  - Accounts for pre-heated machine state in continuous production
- **Cook Time:** 66–77 seconds (optimal: 71 seconds)
  - Reduced from initial default of 105 seconds
  - Balances sugar caramelization with energy efficiency
  - Prevents overcooking that leads to crystallization
- **Cooldown Time:** 54–57 seconds (optimal: 55 seconds)
  - Slightly reduced from default 60 seconds
  - Prevents residual sugar burning in subsequent runs
  - Optimizes cycle time for batch production

Environmental Adaptation Strategy

For challenging environmental conditions (low humidity or temperature), the following parameter adjustments are recommended:

- **Low Before Turn-On Conditions** (humidity ≤ 33% or temperature ≤ 26°C):
  - Wait Time: Increase to 45–50 seconds
  - Cook Time: Increase to 72–75 seconds
  - Cooldown Time: Maintain 55–57 seconds

These bounds represent a 32% reduction in total cycle time compared to initial parameters while maintaining quality scores above 70 points.

Production Phase Temperature Control

Analysis of the machine head temperature during active cotton candy production revealed critical temperature thresholds for quality optimization. The infrared object sensor (`after_flow_start_env_IrO`) monitoring the spinning head temperature during sugar flow provides real-time feedback for production quality control.

Optimal Temperature Bounds. Machine learning analysis identified a narrow temperature window that produces consistently high-quality cotton candy:

- **Target Range:** 74.5–76.0°C (optimal production temperature)
  - Produces quality scores of 70+ points
  - 42.1% success rate for high-quality samples (≥65 points)
  - Average quality score: 68.2 points in this range
- **Acceptable Range:** 74.0–76.5°C (good quality zone)
  - Maintains acceptable quality with minor variations
  - Provides operational flexibility for temperature fluctuations
- **Critical Thresholds:** < 70°C or > 77°C (intervention required)
  - Below 70°C: Poor quality (average 33.1 points, 0% high-quality rate)
  - Above 76°C: Risk of overheating and sugar crystallization

Temperature Progression Analysis. The analysis revealed optimal temperature progression patterns from machine startup to active production:

- **Pre-production temperature:** 55–60°C (`before_turn_on_env_IrO`)
- **Production temperature:** 74.5–76.0°C (`after_flow_start_env_IrO`)
- **Temperature increase:** +15–19°C during transition to production

This temperature progression ensures proper sugar melting without overcooking, achieving optimal cotton candy formation.

Real-time Temperature Control Strategy. For implementation in the next 100 iterations, the following temperature control logic will be applied:

Table 3
Production phase temperature control strategy

Temperature Range	Action	Quality Level	Strategy
< 70°C	Increase heating	Poor	More heating
70–74°C	Monitor closely	Moderate	Standard
extbf74–76°C	**Maintain**	**Excellent**	**OPTIMAL**
> 76°C	Reduce heat	Risk zone	Cool down

This real-time temperature monitoring enables dynamic process adjustment to maintain optimal production conditions throughout each cotton candy cycle.

Implementation for Next 100 Iterations

The optimized parameter bounds will be implemented in the next 100 production iterations to validate their effectiveness in practice. The digital twin system will:

1. Apply the parameter bounds as constraints in the decision tree optimization
2. Monitor quality outcomes to confirm the 70+ quality score target is maintained
3. Track energy consumption reduction compared to baseline parameters
4. Collect additional environmental sensor data to refine the adaptation strategy
5. Document any edge cases requiring parameter adjustments beyond the established bounds

This implementation phase will serve as final validation that the machine learning-derived parameter optimization translates to consistent quality improvements in real-world production scenarios.

Evaluation

Product Output Quality

Test for github of changing things here

The quality of the cotton candy produced in each run was assessed using the previously introduced weight and volume-based metrics. In particular, changes in product volume and the derived Fluffiness Index were analyzed across multiple runs to evaluate whether the digital twin contributed to a measurable improvement in output quality.

Evaluation Methodology and Test Batches

To validate the effectiveness of the digital twin system, we conducted a comprehensive evaluation using dedicated test batches separate from the training data. This evaluation phase, commonly referred to as *test set evaluation* in machine learning, ensures unbiased assessment of the digital twin's predictive capabilities and optimization performance.

The evaluation methodology consisted of three distinct phases:

Phase 1: Predictive Accuracy Assessment We executed a series of production runs while monitoring environmental conditions and process parameters in real-time. For each run, the digital twin system predicted the expected quality score before production began. These predictions were then compared against the actual measured quality metrics (weight, volume, and derived Fluffiness Index) to assess the accuracy of the digital twin's predictive model. This comparison allowed us to quantify the prediction error and evaluate the reliability of the quality forecasting capabilities.

Phase 2: Comparative Analysis with Baseline System In parallel, we implemented and tested the simple control function originally developed for the CPEE (Cloud Process Execution Engine) system. This baseline approach relies on basic parameter thresholds without machine learning optimization. For identical environmental conditions and input parameters, we compared the performance of both systems in terms of quality prediction accuracy and optimization recommendations. This comparative analysis demonstrates the added value of the digital twin approach over conventional rule-based control systems.

Phase 3: Environment Replication and Validation The final evaluation phase involved replicating specific environmental conditions that occurred during previous production runs. Using the recorded sensor data from earlier batches, we recreated similar temperature, humidity, and process parameter combinations. The digital twin system then provided optimization recommendations for these replicated scenarios, and we executed production runs following these recommendations. The resulting quality metrics were compared against both the digital twin's predictions and the actual historical results from the original conditions, validating the system's ability to reproduce and improve upon past performance.

Each evaluation batch consisted of multiple production runs under controlled conditions, with comprehensive data logging to ensure reproducible results. The statistical analysis of these evaluation batches provides quantitative evidence of the digital twin's effectiveness in cotton candy quality optimization and process control reliability.

Product Output Consistency

Like we saw in the research, the less the max pressure of the sugar the better quality the cotton candy.

the smaller the cc, the less quality (when count is)

After count >= 10 its a bad score (too small)

Discussion

Measurement Limitations

While the estimation of product volume provided useful insights into structural quality, it is subject to several limitations. The irregular shape and delicate structure of cotton candy introduce measurement uncertainty, especially when relying on manual tools such as a ruler. Furthermore, the assumption of an ideal oblate spheroid shape simplifies the actual morphology, which may vary significantly across runs.

Despite these limitations, the same procedure was applied consistently throughout the experiments, ensuring the validity of comparative trends. For future work, more precise volume estimation techniques such as 3D scanning or photogrammetric analysis could be explored to capture the complex geometry of the product more accurately.

Answering Research Question 4

How transferable and generalizable are the methods and insights derived from the Cotton Candy Automata digital twin to other process environments?

Let us recall Research Question 4 (**??**), which investigates whether the bottom-up methodology developed in this thesis can be applied beyond the cotton candy case. While the empirical focus is limited to a single robotic system, the approach is designed at an abstraction level (defined in terms of inputs, controls, states, outputs, and constraints) that allows for transferability to other thermo-transformative processes. We provide a conceptual mapping to popcorn production as a demonstration case.

Conceptual Mapping. In line with the Digital Twins of Business Processes: A Research Manifesto [6], digital twins operate at the intersection of the *Physical Space* and the *Digital Space*. The physical space includes both the *system* (machines, materials, actuators) and the *environment* (contextual conditions such as temperature and humidity), which are captured by sensors and mirrored digitally. The manifesto emphasizes that meaningful twins must incorporate both aspects to provide actionable decision support. This distinction is reflected in the abstraction adopted in this thesis: *Inputs and Controls* correspond to the physical system, while **States** represent the environment and system conditions that cannot be directly manipulated but exert significant influence on outcomes.

Table 4

Conceptual mapping of the bottom-up digital twin approach from cotton candy to popcorn.

Abstraction Layer	**Cotton Candy Automata**	**Popcorn Process**
Physical System (Inputs)	Sugar type and amount	Kernel type and amount, oil amount
Physical System (Controls)	Heater temperature, spinning duration, cooling temp	Heater temperature, oil preheating, shaking/venting pattern
Environment (States)	Inner pot temperature, ambient temperature and humidity	Pot/oil temperature, ambient temperature, steam release, acoustic pop rate
Outputs (KPIs)	Cotton candy mass, product quality (texture, stickiness), energy usage, total time	Popped mass, unpopped kernels, burnt kernels, energy usage, total time
Constraints	Safety temperature limits, motor stability	Oil smoke point, fire risk, safety temperature limits

.

The table distinguishes between the *physical system* (inputs and controls) and the *environment* (states), following the perspective of the [6, Digital Twins of Business Processes: A Research Manifesto]

Application to Popcorn. To demonstrate transferability, the Cotton Candy Automata methodology was conceptually mapped to another thermo-transformative process: popcorn production. Both processes rely on heat-induced material transformation, where quality and efficiency depend on precise control of time, temperature, and environmental conditions. In cotton candy, the digital twin tracks sugar input, heating duration and temperature to optimize yield, energy use, and product texture. In popcorn, analogous parameters can be identified: kernel mass and oil quantity as inputs, heater duty cycle and venting pattern as controls, and acoustic pop rate and steam release as environmental states. Outputs such as unpopped kernels, burnt kernels, and energy per gram popped are directly comparable to the quality, energy, and throughput metrics in cotton candy.

Answer to RQ4. The comparison demonstrates that the bottom-up digital twin approach is not locked to a single system but generalizable to structurally similar processes. By abstracting system-specific details into layers of *Inputs, Controls, States, Outputs, and Constraints*, the methodology provides a template that can be applied across domains. While the empirical implementation in this thesis focuses on cotton candy, the conceptual extension to popcorn shows that the same modeling and optimization principles can be applied with minimal methodological adjustments. This aligns with the manifesto's claim that digital twins must integrate both physical and environmental factors to support prescriptive decision-making [6]. Therefore, the results of this thesis have broader relevance for other small-scale thermo-transformative processes (e.g., roasting, baking, drying), indicating that the developed approach has the potential to inform digital twin design beyond the specific case of cotton candy.

Reflections and Lessons Learned

A Digital Twin Model without Sensors: In hindsight, I would have begun by training a digital twin model relying solely on cook time, wait time, and cooldown time, excluding sensor data. This approach would have enabled a quick baseline without the delay of configuring and testing sensors. Initial quality scores could have been manually classified into three categories (bad, okay, and good) to identify basic patterns. Although subjective, this early data might have reduced the number of batches required for fine-tuning once sensor data became available and before the quality scoring was automated.

However, it remains unclear whether this strategy would have accelerated model development. Since the process proved complex enough, reliable sensor data for temperature measurements was indispensable. Moreover, thorough evaluation still required multiple production cycles, each taking approximately ten minutes, limiting the extent to which this shortcut could have reduced overall effort.

Reflections on CPEE Expressiveness: Extracting features from the CPEE model logs was challenging, as they often contained more than 70,000 lines and thousands of events. Each model update required a new extraction script that had to be implemented and tested, making the process cumbersome. In retrospect, a more efficient solution would have been to add a single script event at the end of each process execution that stored all relevant data elements in the log (e.g., in the third-to-last event). This would have allowed the extraction code to access the required values directly, rather than iterating through the entire log. Likewise, storing derived values such as time differences within data elements would have eliminated the need for additional post-hoc calculations.

A True Prescriptive Digital Twin

The implementation developed in this thesis represents a step toward, but does not yet achieve, a fully prescriptive digital twin. In its current state, the system provides a functional model of the production process; however, it does not autonomously update and refine itself at regular intervals as new data becomes available. In other words, the digital twin is not yet self-actualizing and does not operate continuously in the background without human intervention.

The prototype includes a service layer that processes each production log by passing it to the digital twin project, allowing historical data to be backtracked and analyzed. Extending this into a complete, continuously updating system would have required at least an additional month of development and testing, as validation of such functionality is particularly time-intensive. Furthermore, we assessed that such an extension would have offered only limited short-term benefits. Continuous operation of the digital twin in tandem with the physical system still requires a human operator to remain in the laboratory for safety supervision and to ensure correct synchronization between the digital model and the physical outcomes (e.g., verifying the exact moments when cotton candy begins and ends production). Each production cycle takes approximately ten minutes, excluding setup, cleaning, and maintenance, which further constrains the pace of testing and iteration. As a result, while our implementation demonstrates the feasibility of prescriptive digital twin concepts, it falls short of achieving full autonomy within the scope of this thesis.

Integrating Live Process Data into the Digital Twin

As part of the system setup, we implemented a lightweight registry service ('cc_registry') running on the Raspberry Pi. The service accepts POST requests from the CPEE whenever a new process instance is started, storing its UUID together with contextual information such as a timestamp and instance URL in a YAML file. A simple Bottle-based web interface then visualizes these records in real time, allowing processes to be tracked, backtracked, and linked directly to their execution logs. This solution ensured that the digital twin could consistently access recent process data without relying on manual configuration or persistent storage overhead. The service was intentionally kept minimalistic, focusing on robustness, retrievability, and transparency of ongoing executions.

While this registry advances the integration of live process data into the digital twin, it remains at the stage of a digital model rather than a fully autonomous prescriptive twin. The system can replay and analyze logs, but it does not yet actualize itself by iteratively retraining or adapting models as new data arrive. This limitation aligns with observations in the literature, where many implementations still lack continuous, bidirectional data flows or real-time adaptation, thereby falling short of Grieves' original definition of a true digital twin. In our case, further automation would have required significantly more testing effort, which was constrained by the physical setting of the cotton candy automata and the need for continuous human supervision during operation.

Towards a Prescriptive Digital Twin

The implementation carried out in this thesis demonstrates the core building blocks of a prescriptive digital twin. We developed a lightweight registry service and data logging infrastructure that ensured reliable access to process executions, integrated real-time measurements of the automata, and implemented a decision tree-based optimization pipeline for parameter tuning. Together, these components allowed the digital twin to analyze past runs, evaluate parameter impacts, and suggest improved configurations.

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e this sentence bet-

Nevertheless, the system still remains at the stage of a digital model rather than a fully autonomous prescriptive twin. While logs can be replayed and optimization applied retrospectively, the twin does not yet actualize itself by continuously retraining or adapting its models as new data arrive. Completing such a feedback loop would have required several additional weeks of testing, which in this project is particularly time-consuming due to the ten-minute execution time per run and the substantial overhead of cleaning, maintenance, and supervision. Furthermore, human presence remains indispensable, both for safety reasons and for monitoring the discrepancy between machine signals and the actual outcome of cotton candy production. Thus, despite infrastructural progress, the twin remains dependent on external intervention. This limitation mirrors what is observed in recent reviews of digital twin applications, where most implementations remain digital models rather than continuously adapting and prescriptive systems [5].

Conclusion

1-2 pages

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Appendix

Table 5

Your first table

Value 1	**Value 2**	**Value 3**
α	β	γ
1	1110.1	a
2	10.1	b
3	23.113231	c

A note describing the table.

Figure 6
My Figure Caption

A note describing the figure