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

TUM

Master's Thesis in Informatics

Nicolás Mario Arteaga García

Cotton Candy Digital Twin: Prescriptive Creation of Digital Twins

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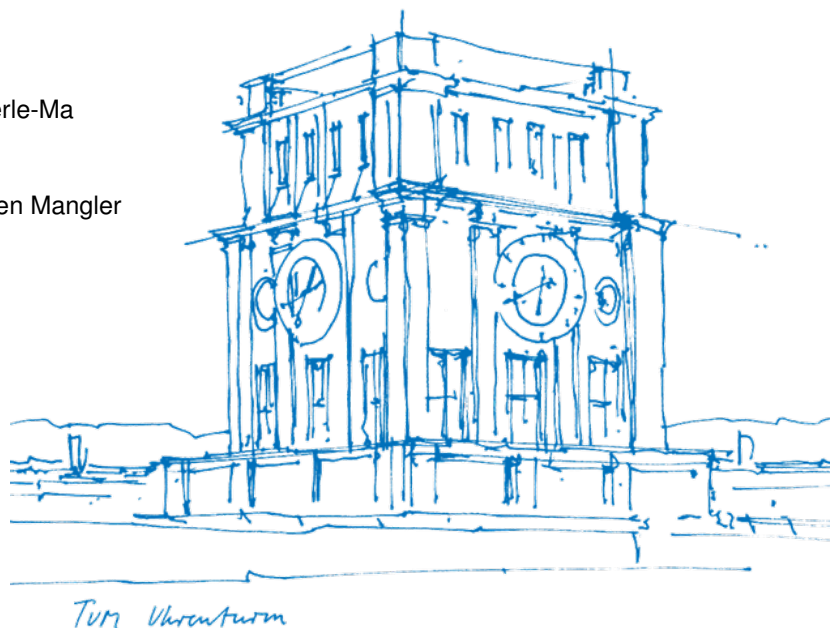
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Submitted on
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TUM Uhrenturm

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Garching, 31.07.2025   Nicolás Mario Arteaga García

Abstract

150 - 180 words

Keywords: Digital Twin, Cotton Candy, BPTM

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

Contents

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Introduction

For exposes, create this chapter, plus start with chapter 2 (Related Work).

Motivation

Why are we doing it? About 1 page.

As industries evolve, the ability to optimize processes while minimizing waste has become increasingly important. Digital twins (virtual models of physical systems) are transforming how we monitor, analyze, and improve these processes. While reactive digital twins respond to events as they occur, providing immediate but limited feedback, predictive digital twins forecast potential outcomes based on historical and real-time data, allowing proactive adjustments. However, the growing focus on prescriptive digital twins introduces a new frontier: systems that not only predict outcomes but also recommend specific actions to achieve goals such as improving efficiency, reducing energy consumption, or enhancing product quality.

This thesis explores the development of prescriptive digital twins using the Cotton Candy Automata, a robotic system developed in the chair to automate cotton candy production, as a practical and measurable test case. This scenario provides an ideal environment for evaluating two distinct approaches to digital twin design—bottom-up and top-down—by analyzing key variables such as heating time, spinning duration, sugar amount, and energy usage. Each approach takes a unique perspective:

Bottom-Up Approach: Focuses on physical measurements and process models, leveraging real-time sensor data to guide system optimization.

Top-Down Approach: Relies on historical data and advanced computational methods, including interpolation, selection of closest historical values, and machine learning models like Recurrent Neural Networks (RNNs), to model and optimize the system.

The goal of this thesis is to provide a comprehensive evaluation of these two approaches, comparing their strengths, limitations, and suitability for different scenarios. By analyzing metrics such as energy savings, time efficiency, and production quality, the research aims to determine which method

offers the greatest value (for this process/for specific process types?). Applying both methodologies to the same scenario enables a deeper understanding of their trade-offs and practical implications, offering insights that can guide future efforts in digital twin development.

Ultimately, this work contributes to the broader understanding of how to design and implement prescriptive digital twins, providing actionable recommendations for selecting the best approach based on system goals, constraints, and operational contexts.

Research Questions

At least 3 questions. They should not be answerable yes/no. Questions should be questions (1 sentence). But you are allowed to explain them in more detail. In the explanation also tell how you plan to prove that your potential future solution is good.

About 1 page.

Fexamples: (1) How can we design and implement prescriptive digital twins for the Cotton Candy Automata? (2) MMM What are the strengths and limitations of each approach, and how do they impact key metrics such as energy savings, time efficiency, and production quality?

Contribution

What will/have I do/done that nobody else has done before. About 1/2 page.

Methodology

Design Science in Information System (Hevner). How are we doing research?

(1) Summary what design science is (it uses stakeholders, artefacts, steps, ...).

(2) What are the stakeholders, artefacts, steps for MY case. What does it mean for my thesis?

About 1.5 pages.

This work follows the Design Science Research (DSR) paradigm as defined by Hevner et al. [1]. The DSR approach provides a structured framework for the development and evaluation of innovative artefacts that solve real-world problems in a rigorous and methodologically grounded manner.

In the context of this thesis, the central artefact is a digital twin system for a cotton candy production robot. This artefact comprises both the virtual representation of the physical process and the accompanying infrastructure for capturing environmental and process-related parameters (e.g., humidity, input sugar, and runtime), as well as metrics of product quality (e.g., volume, weight, and fluffiness).

The digital twin is iteratively refined through cycles of design and evaluation, in accordance with the DSR methodology. The system is deployed in a real-world production context and evaluated based on its ability to improve product quality and production efficiency under varying conditions. This dual focus on practical applicability and measurable improvement ensures that the artefact addresses both relevance and rigour — the core criteria of Hevner's framework.

Evaluation

How will I evaluate that my proposal is good. This ties into the research questions.

About 1 page.

Structure

Which chapters will my thesis have, and what are they all about. About 1/4 page.

Related Work

Related Work - There is a girl with long dark hair doing a thesis on digital twin as a research analysis. ask her per discord

google scholar in-title digital twin / business processes, search queries that give you less than 20 papers and decide 1 or 2 papers in the end. How many papers did we eliminate? why? bc too

backgorund 1-2 sentences -> Why am I doing something different to this related work

Final max 4-5 papers that really relate to what Im doing

THis one doesnt work bc, its for bridges and civil engineering https://www.sciencedirect.com/science/article/pii/S0141029623

this one looks good : https://www.sciencedirect.com/science/article/pii/S0360835224003620

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.

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

 • **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.

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.

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 1
My Figure Caption

A note describing the figure

Implementation

Automata

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

Sugar Amount

To calibrate the sugar dispensing system, we measured ten times the amount of sugar released over durations of 0.5s, 1s, 1.5s and 2s (2s slightly overflowed the spoon)with each setting tested in multiple trials. The resulting median values 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 efforts, we standardized the input to 1s of sugar dispensing so 12.63g.

Waiting Time

The time the robot arm waits until sugar starts flowing out of the spinner. The cold start time was a variable used for the first time (102s) with an environment of 25C, our digital twin will leave this variable unneeded. Since it will already know how to act with the actual temperature of the spinner. At the end of the thesis we will see the variance of this time, based mostly on how warm the spinner will be before.

Cooking Time

The default cooking time is 105s. This starts once the sugar starts flowing out of the spinner. probably becuase 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 is the time that the spinner runs without the heat, to cool down after the production run. This is needed to avoid burning the sugar in the next run. The default cooldown time is 60s, but we are gonna research how good the quality is gonna be if we increase or decrease this value. The Machine manual empfehlen to wait 120s, but we started with 60s bc we noticed a lot room for improvement while using the automata and sometimes it takes a long time to start the next process again to put the sugar and turnon the machien again makes it roughly 120s anyway.

Cotton Candy iteration

We are gonna store which cotton candy iteration we are on, since the last time the machine has been cleaned. We already noticed what a big difference it can make on the quality when the machine has run for a long time without cleaning. We want to find the optimal value of iterations we want to run before cleaning the machine. We will start with max 20 iterations. We will clean the machine and declog the sugar of the spinner with water.

Energy Consumption Measurement

Energy consumption is measured and stored for each production cycle to enable optimization of process parameters for energy efficiency. This measurement, combined with quality metrics, allows the digital twin system to find optimal parameter settings that minimize energy consumption while maintaining 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 result is converted from Watt-seconds to Watt-hours for practical interpretation of the 5-minute production cycles.

This methodology captures energy consumption across all production phases (startup, heating, spinning, 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 weights 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 2

Comparison between geometric approximation and real cotton candy morphology
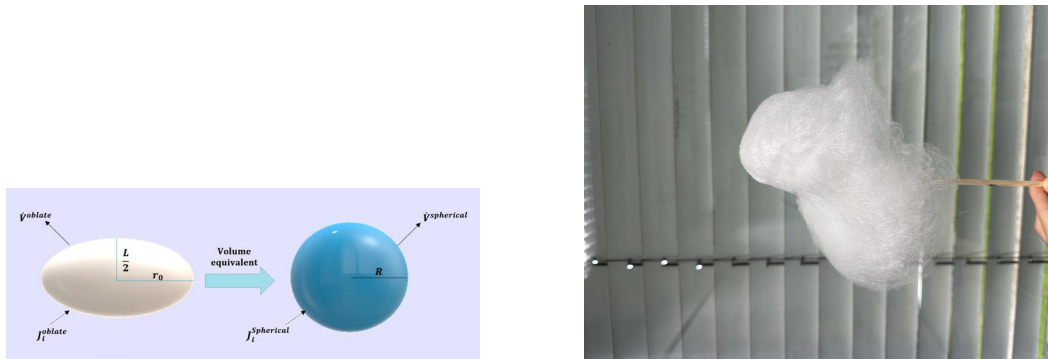
(a) *Idealized oblate spheroid*

(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.

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.

Figure 3

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.
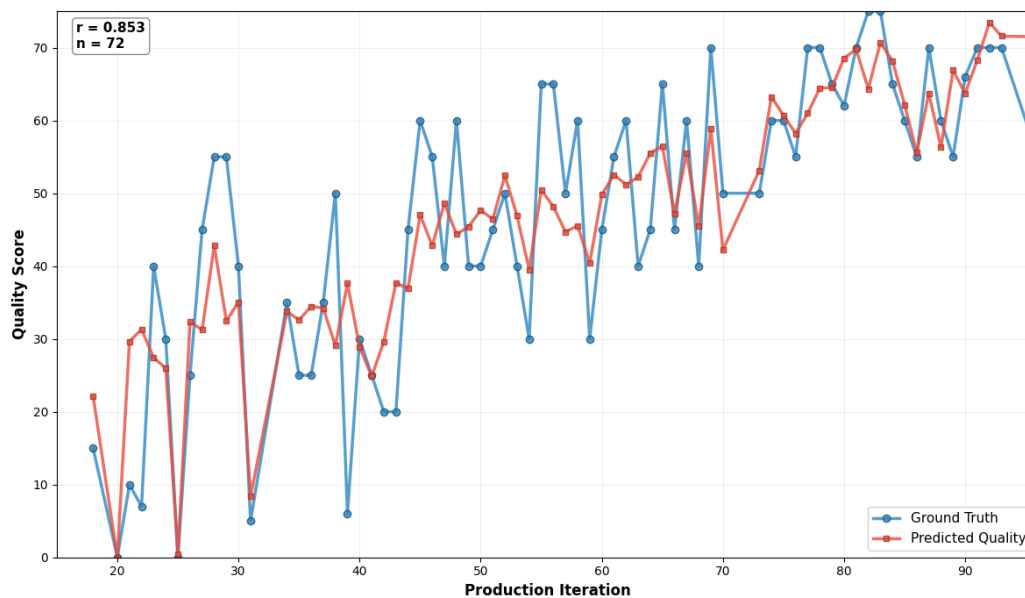
The algorithm successfully captures both the learning progression evident in early iterations and the

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.

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 parame

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 1
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
74–76°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.

What Would I Have Done Differently?

I would have begun by training a decision tree with a digital twin that excluded sensors, relying solely on cook time, wait time, and cooldown time. This would have enabled a quick baseline without the delay of setting up and testing sensors. The initial quality scores could have been manually classified into three categories—bad, okay, and good—sufficient 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.

Conclusion

Bibliography

[1] A. R. Hevner, S. T. March, J. Park, and S. Ram, "Design science in information systems research," *MIS Quarterly*, vol. 28, no. 1, pp. 75–105, 2004. DOI: `10.2307/25148625`.

[2] M. J. Zaki and W. M. Jr., *Data Mining and Machine Learning: Fundamental Concepts and Algorithms*, 2nd. Cambridge University Press, Mar. 2020, ISBN: 978-1108473989.

Appendix

Table 2
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 4
My Figure Caption

A note describing the figure