Digital Twin and Simulation-Based Design of Agricultural Processing Equipment

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Field: Mechanical Engineering; Agricultural Processing Machinery; Industrial Machinery; Simulation-Based Design; Digital Twin Systems; Cotton Processing Equipment

Abstract

Agricultural processing equipment plays a critical role in transforming raw agricultural materials into usable industrial inputs. In cotton processing, grain handling, seed cleaning, fiber preparation, and other post-harvest operations, machinery must process biological materials that are variable in moisture, size, density, contamination level, mechanical strength, and flow behavior. This variability creates engineering challenges related to throughput, cleaning efficiency, energy consumption, material loss, machine wear, equipment reliability, and product quality.

This article proposes a digital twin and simulation-based design framework for agricultural processing equipment, with particular emphasis on cotton cleaning, cotton separation, and raw material handling machinery. The proposed framework connects physical equipment, sensor data, simulation models, process optimization, and design feedback into an integrated engineering system. Instead of relying only on physical prototyping or trial-and-error modification, engineers can use digital twin models to evaluate machine geometry, operating speed, material flow, cleaning performance, energy demand, and failure risk before or during equipment operation.

The article presents a conceptual digital twin architecture, a simulation-based design workflow, key input and output parameters, performance indicators, an illustrative evaluation matrix, and future research directions. The framework is designed to support agricultural processing machinery modernization, industrial automation, predictive maintenance, and sustainable manufacturing. It is especially relevant to cotton processing equipment, where improved machinery design can reduce processing losses, improve raw material quality, increase energy efficiency, and support more resilient agricultural manufacturing systems.

Keywords: digital twin; agricultural processing machinery; cotton processing equipment; simulation-based design; industrial machinery; mechanical engineering; smart manufacturing; predictive maintenance; material flow; process optimization.

1. Introduction

Agricultural processing equipment is essential to modern industrial production because it transforms raw agricultural materials into usable intermediate or final products. Cotton, grain, seeds, fibers, and other agricultural materials often require cleaning, separation, drying, conveying, sorting, and mechanical preparation before they can be used in manufacturing or food, textile, and industrial supply chains.

Unlike many uniform industrial materials, agricultural raw materials are biologically variable. Their mechanical and physical properties may change according to moisture content, harvesting method, storage conditions, contamination level, maturity, fiber structure, density, and the presence of foreign matter. This variability makes agricultural processing equipment difficult to design and optimize. A machine that performs well under one material condition may produce excessive losses, low cleaning efficiency, high energy consumption, or mechanical damage under another condition.

Cotton processing is a representative example of this problem. Seed cotton may contain stems, leaves, dust, soil particles, immature fibers, and other foreign matter. It may also vary in moisture, density, fiber attachment, and flow behavior. Cleaning and separation equipment must therefore remove impurities while minimizing damage to fiber and seeds. Prior research by Pirnazarov (2021) addressed the design and development of seed cotton pre-cleaner machinery and emphasized the importance of machine design for improving cotton cleaning technology.

Digital twin technology provides a new opportunity to improve agricultural processing equipment design. A digital twin can be understood as a connected virtual representation of a physical product, process, or system that uses data and simulation to monitor, analyze, predict, and optimize system behavior. In manufacturing research, digital twins have been widely discussed as enabling tools for smart manufacturing, product design, production optimization, predictive maintenance, and lifecycle management (Tao et al., 2018; Negri et al., 2017; Kritzinger et al., 2018; Tao et al., 2019; Jones et al., 2020; Fuller et al., 2020).

The purpose of this article is to propose a digital twin and simulation-based design framework for agricultural processing equipment. The framework is intended to support the design, optimization, and practical modernization of machinery used in cotton processing, seed cleaning, raw material handling, and related agricultural manufacturing systems.

2. Technical Background

2.1 Agricultural Processing Equipment as a Variable-Material Engineering System

Agricultural processing equipment differs from many conventional mechanical systems because the processed material is not uniform. Raw agricultural materials may vary from batch to batch and even within the same batch. In cotton processing, for example, seed cotton may contain different levels of foreign matter, variable moisture content, non-uniform fiber attachment, and irregular material flow behavior. These properties directly influence cleaning efficiency, separation quality, energy consumption, machine loading, and wear.

From an engineering perspective, agricultural processing equipment can be treated as a material-machine interaction system. The machine applies mechanical forces to the raw material, while the material responds through movement, separation, deformation, breakage, compression, or flow obstruction. This interaction determines whether the equipment achieves the desired processing outcome.

A high-performing agricultural processing machine should maintain stable throughput, remove unwanted material, preserve useful product quality, reduce material loss, minimize energy consumption, limit mechanical wear, and operate reliably under variable material conditions. Achieving all of these objectives simultaneously requires systematic modeling and design optimization.

2.2 Digital Twin Concepts in Manufacturing

Digital twin technology has become an important concept in smart manufacturing and Industry 4.0. Tao et al. (2018) proposed digital twin-driven product design, manufacturing, and service with big data. Kritzinger et al. (2018) classified digital model, digital shadow, and digital twin according to the level of integration between physical and virtual systems. Negri et al. (2017) reviewed the role of digital twins in cyber-physical production systems, while Tao et al. (2019) reviewed the state of digital twin research in industry. Jones et al. (2020) characterized the digital twin concept through a systematic literature review, and Fuller et al. (2020) discussed enabling technologies, challenges, and open research questions.

For agricultural processing equipment, a digital twin may include a virtual model of machine geometry, material flow, mechanical motion, process parameters, sensor data, performance indicators, maintenance status, and predicted output quality. The value of such a system is not limited to visualization. A digital twin can support engineering decisions by predicting how equipment will behave under changing material and operating conditions.

2.3 Simulation-Based Design

Simulation-based design allows engineers to evaluate machine concepts before constructing or modifying physical equipment. In agricultural processing machinery, simulation can be used to evaluate material flow, cleaning performance, machine loading, energy consumption, vibration, component wear, and process stability.

A simulation model may be developed using different methods depending on the engineering question. Mechanical system simulation can represent rotating components, drives, shafts, bearings, frames, and dynamic loads. Material flow simulation can represent movement, separation, and accumulation of cotton, seeds, fibers, or foreign matter. Process simulation can estimate throughput, cleaning efficiency, losses, and energy demand. Reliability simulation can estimate wear, maintenance needs, and potential failure points.

Verification and validation are essential for simulation-based design. Sargent (2013) emphasized the importance of verifying and validating simulation models so that they can be used reliably for decision-making. In agricultural processing machinery, validation may require comparing model predictions with laboratory tests, prototype measurements, production data, or controlled equipment trials.

3. Objective and Contribution of the Article

The objective of this article is to propose a practical framework for applying digital twin and simulation-based design methods to agricultural processing equipment.

The proposed framework contributes to the field in three ways.

First, it organizes agricultural processing machinery design as a connected physical-virtual system rather than as an isolated mechanical design problem.

Second, it identifies the key engineering parameters required to build a useful digital twin for cotton processing and related equipment.

Third, it presents a structured workflow for using simulation, sensor data, and performance indicators to improve machine design, operational efficiency, and maintenance planning.

The framework is especially relevant to cotton cleaning and separation machinery, but it may also be applied to grain cleaning systems, seed processing equipment, fiber handling systems, conveying machinery, and other agricultural processing technologies.

4. Proposed Digital Twin Architecture for Agricultural Processing Equipment

A digital twin for agricultural processing equipment should include five connected layers: the physical equipment layer, the sensing and data acquisition layer, the simulation and analytics layer, the decision-support layer, and the feedback and optimization layer.

The physical equipment layer includes the agricultural processing machine itself, such as a cotton pre-cleaner, cotton separator, seed cleaner, conveyor, feeder, or cleaning drum. The sensing and data acquisition layer collects information about material conditions, machine operating state, process output, vibration, load, speed, temperature, energy consumption, and maintenance condition. The simulation and analytics layer uses this information to estimate material flow, cleaning efficiency, machine stress, component wear, and process stability. The decision-support layer evaluates performance indicators and recommends design or operating changes. The feedback and optimization layer connects the virtual model back to machine design, process control, maintenance planning, or future equipment development.

This layered structure is consistent with the general use of digital twins as connected physical-virtual systems for design, manufacturing, monitoring, and service optimization (Tao et al., 2018; Kritzinger et al., 2018).

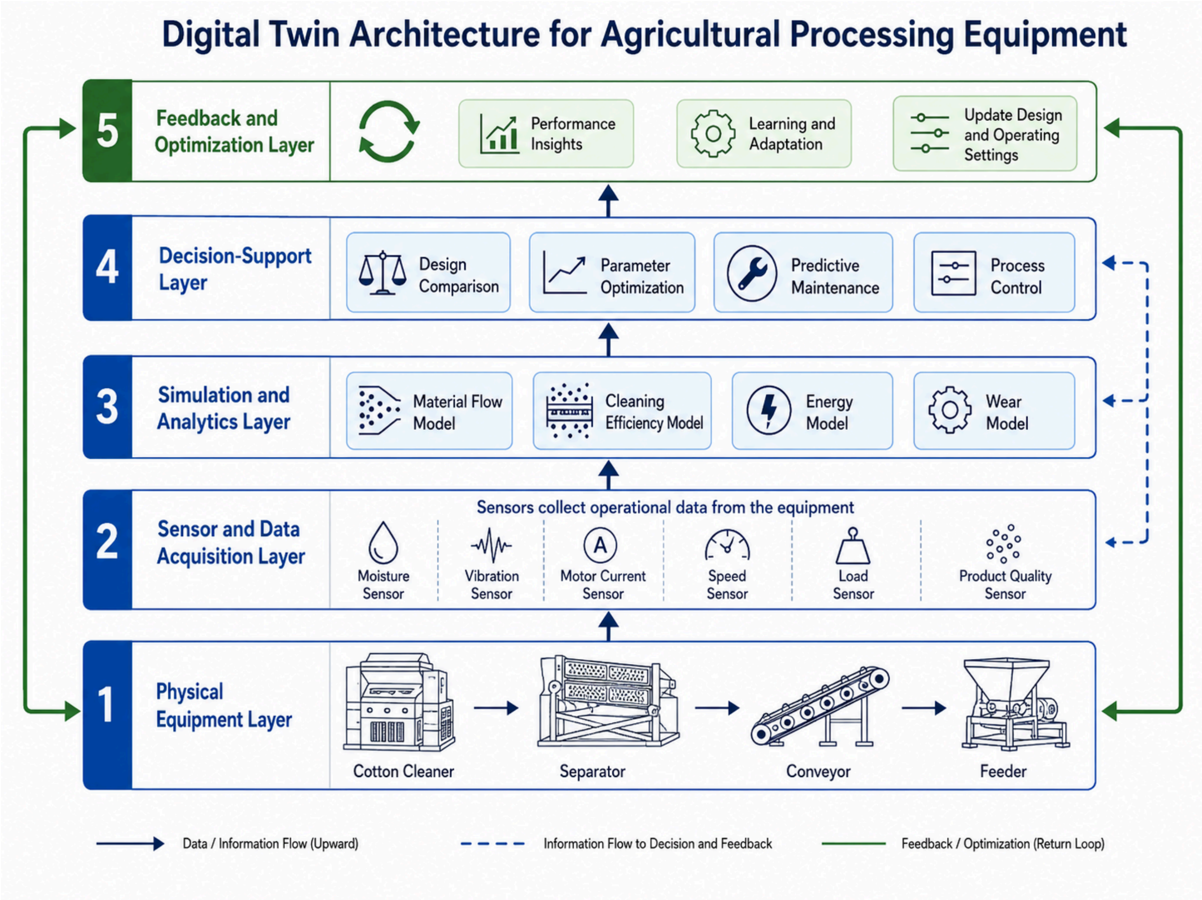

Figure 1. Digital Twin Architecture for Agricultural Processing Equipment

5. Key Parameters for the Digital Twin Model

A digital twin for agricultural processing equipment should include both machine-side and material-side parameters. Table 1 summarizes the most important parameters for a digital twin model of cotton processing or similar agricultural processing equipment.

Table 1. Key Parameters for Digital Twin Modeling of Agricultural Processing Equipment

Category	Parameter	Engineering Meaning	Role in Digital Twin
Raw Material	Moisture content	Water content of cotton, seed, or agricultural material	Influences flow, adhesion, cleaning, and energy demand
Raw Material	Foreign matter content	Amount of unwanted material before processing	Determines required cleaning intensity
Raw Material	Bulk density	Mass per unit volume of material stream	Affects feeding rate and machine loading
Raw Material	Particle or fiber size distribution	Distribution of material sizes and shapes	Influences separation and cleaning behavior
Raw Material	Mechanical sensitivity	Tendency of useful material to be damaged	Important for quality preservation
Machine	Drum or rotor speed	Rotational operating speed	Influences cleaning force, throughput, and damage risk
Machine	Feed rate	Mass flow entering the machine	Determines throughput and loading
Machine	Clearance settings	Distance between working components	Influences separation and material damage
Machine	Screen or grid geometry	Openings and contact geometry	Controls separation and foreign matter removal
Machine	Motor current	Electrical load of the drive system	Indicates energy use and overload risk
Machine	Vibration level	Dynamic response of the equipment	Indicates imbalance, wear, blockage, or instability
Process Output	Cleaning efficiency	Reduction of foreign matter after processing	Main process performance indicator

Process Output	Material loss	Useful material removed or damaged during processing	Important for economic and quality performance
Process Output	Specific energy consumption	Energy required per processed mass	Measures energy efficiency
Process Output	Product quality	Fiber, seed, or material condition after processing	Indicates whether processing is too aggressive
Maintenance	Wear rate	Degradation of machine components	Supports predictive maintenance
Maintenance	Failure probability	Estimated risk of malfunction	Supports reliability planning

These parameters should not be treated as independent. For example, increasing rotor speed may increase cleaning efficiency but may also increase energy consumption, vibration, wear, and material damage. Increasing feed rate may improve productivity but may reduce cleaning quality or increase blockage risk. Digital twin modeling is useful because it allows engineers to evaluate these trade-offs before making physical design changes.

6. Simulation Modules for Agricultural Processing Equipment

A practical digital twin should include several simulation modules. The first module is a machine kinematics and dynamics model that represents moving components, drive systems, rotational speed, load distribution, vibration, and mechanical stability. The second module is a material flow model that represents how cotton, seed, grain, or other agricultural material moves through the machine. The third module is a cleaning or separation model that estimates how foreign matter is removed and how useful material is retained. The fourth module is an energy model that estimates motor load, power demand, and energy per processed mass. The fifth module is a reliability and maintenance model that estimates wear, imbalance, blockage, and failure probability.

The exact modeling method depends on equipment type and available data. Early design studies may use simplified analytical models or reduced-order simulation. More advanced systems may integrate multi-body dynamics, discrete element modeling, computational fluid dynamics, sensor data, and machine learning. However, increasing model complexity is not always beneficial. The model should be as detailed as necessary for the engineering decision being made.

Model complexity should also be balanced with verification, validation, and intended use, because simulation credibility depends on whether the model is sufficiently accurate for the decision it supports (Sargent, 2013).

7. Google Docs-Friendly Performance Formulas

The following formulas are written in plain text format so they can be inserted directly into Google Docs without equation formatting problems.

7.1 Throughput

Machine throughput can be expressed as:

Q = mprocessed / t

In this expression, **Q** represents throughput, **mprocessed** represents the mass of agricultural material processed by the machine, and **t** represents processing time.

7.2 Cleaning Efficiency

Cleaning efficiency can be expressed as:

CE = ((FMin - FMout) / FMin) × 100%

In this expression, **CE** represents cleaning efficiency, **FMin** represents the foreign matter content before processing, and **FMout** represents the foreign matter content after processing.

7.3 Material Loss

Material loss can be expressed as:

ML = (mloss / min) × 100%

In this expression, **ML** represents material loss, **mloss** represents the mass of useful material lost during processing, and **min** represents the mass of useful material entering the machine.

7.4 Specific Energy Consumption

Specific energy consumption can be expressed as:

$$SEC = E_{total} / m_{processed}$$

In this expression, **SEC** represents specific energy consumption, **Etotal** represents total energy consumed during processing, and **mprocessed** represents the mass of processed material.

7.5 Digital Twin Prediction Error

Digital twin prediction error can be expressed as:

$$E_{error} = |Y_{measured} - Y_{predicted}| / Y_{measured} \times 100\%$$

In this expression, **Eerror** represents the prediction error of the digital twin, **Ymeasured** represents the measured value from the physical machine, and **Ypredicted** represents the value predicted by the digital twin model.

7.6 Multi-Objective Optimization Score

A simplified multi-objective optimization score can be expressed as:

$$F_{score} = \alpha CE + \beta Q - \gamma ML - \delta SEC - \eta E_{error}$$

In this expression, **Fscore** represents the overall optimization score, **CE** represents cleaning efficiency, **Q** represents throughput, **ML** represents material loss, **SEC** represents specific energy consumption, **Eerror** represents digital twin prediction error, and **α, β, γ, δ, and η** represent weighting coefficients selected according to design priorities.

This expression is conceptual and should be calibrated for a specific machine, process, and operating environment. For example, if product quality is more important than maximum throughput, the weighting factor for material loss may be increased. If energy efficiency is the main priority, the weighting factor for specific energy consumption may be increased.

8. Simulation-Based Design Workflow

The proposed simulation-based design workflow begins with defining the target machine function and the processed material. In a cotton pre-cleaner, the main function may be removal of foreign matter while preserving fiber and seed quality. In a seed cleaner, the main function may be separation by size, density, or aerodynamic behavior. In a conveyor, the main function may be stable and uniform material transfer.

The second step is to identify the main design variables, including machine geometry, rotor speed, screen openings, clearance settings, feeding mechanism, air flow if applicable, and drive configuration. The third step is to create a baseline simulation model that represents the machine and material flow. The fourth step is to validate the model using available experimental or operational data. The fifth step is to perform design experiments by changing key parameters and observing effects on throughput, cleaning efficiency, material loss, energy consumption, and vibration. The sixth step is to select a preferred design configuration based on multi-objective performance. The final step is to update the digital twin with new data from prototype testing or operation.

This workflow allows design improvement to become a continuous process rather than a one-time equipment modification.

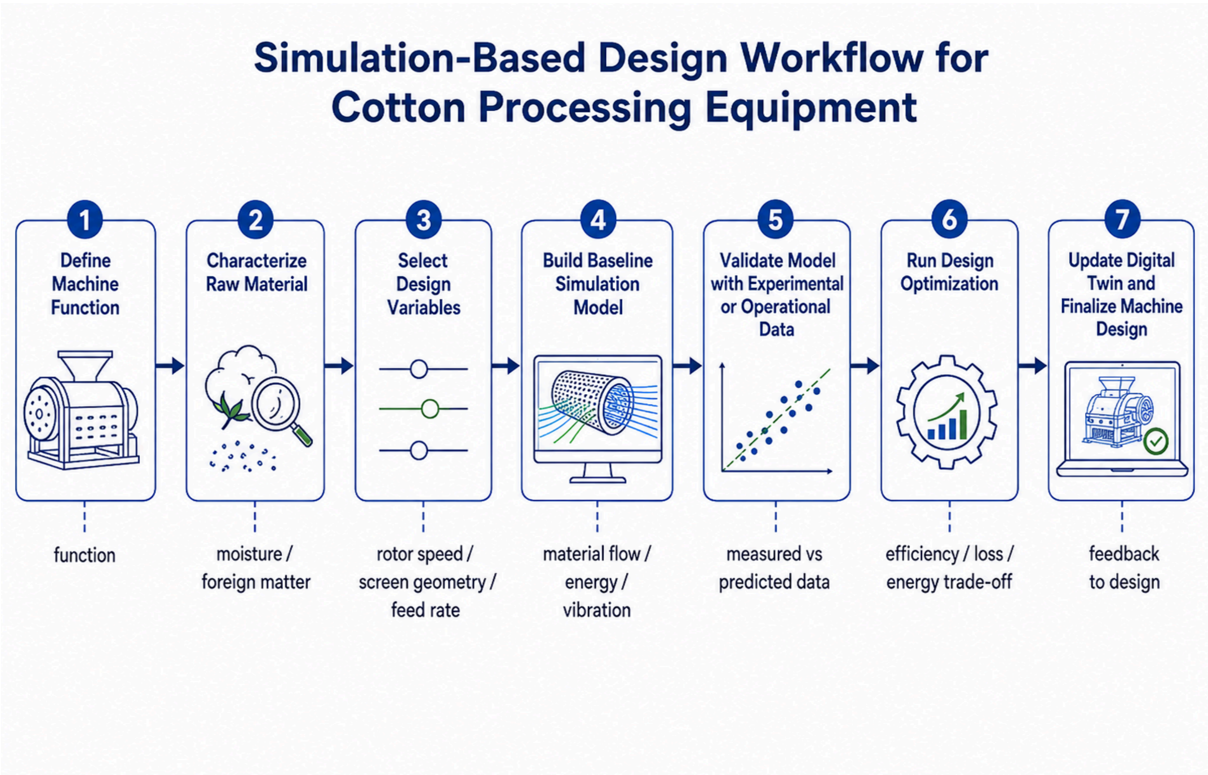

Figure 2. Simulation-Based Design Workflow for Cotton Processing Equipment

9. Illustrative Digital Twin Data Structure

A useful digital twin requires a structured data model. Table 2 presents an illustrative data structure for agricultural processing equipment. The table is conceptual and should be adapted to the specific machine type.

Table 2. Illustrative Data Structure for a Digital Twin of Agricultural Processing Equipment

Data Layer	Example Data	Collection Method	Use in Digital Twin
Material Input Data	Moisture, foreign matter, bulk density, material size distribution	Laboratory test, sensor data, batch inspection	Predict processing difficulty and required settings
Machine Configuration Data	Rotor geometry, screen size, clearances, feed mechanism, drive system	CAD model, machine specification, design files	Build simulation model and compare design options
Operating Data	Rotor speed, feed rate, motor current, vibration, temperature	Sensors, PLC, operator logs	Monitor equipment state and process stability
Output Quality Data	Remaining foreign matter, fiber damage, useful material loss, product uniformity	Sampling, imaging, laboratory analysis	Evaluate cleaning and separation performance
Energy Data	Power consumption, operating time, specific energy use	Motor sensors, energy meters	Optimize energy efficiency
Maintenance Data	Wear condition, vibration trends, blockage events, downtime	Inspection, sensors, maintenance logs	Predict failure and plan maintenance
Model Data	Simulation parameters, calibrated coefficients, prediction error	Digital twin software and validation process	Improve model accuracy over time

This structure allows the digital twin to connect design information, operational data, and process performance. Without structured data, a digital twin may become only a visualization tool rather than a practical engineering decision-support system.

10. Application to Cotton Cleaning and Separation Machinery

Cotton cleaning and separation machinery is a strong candidate for digital twin and simulation-based design because the process involves variable material properties, multiple mechanical interactions, and a need to balance cleaning efficiency with quality preservation. Seed cotton may include useful fibers and seeds together with unwanted plant fragments, dust, stems, leaves, soil, and other foreign matter. The equipment must separate these materials without applying excessive mechanical force that could damage the useful product.

In a digital twin of cotton cleaning machinery, the machine model may include feeding rollers, cleaning drums, grid bars, screens, conveyors, air channels, and drive components. The material model may include cotton mass flow, foreign matter distribution, moisture content, bulk density, and probability of separation. The performance model may estimate cleaning efficiency, useful material loss, energy consumption, vibration, blockage risk, and wear.

Prior work on seed cotton pre-cleaner machinery demonstrates the relevance of machine design to cleaning performance and raw material quality (Pirnazarov, 2021). A digital twin framework can extend this type of machinery research by allowing multiple machine configurations to be compared virtually before physical prototyping.

Table 3. Digital Twin Use Cases for Cotton Processing Equipment

Use Case	Digital Twin Function	Expected Engineering Benefit
Design comparison	Compare alternative drum, screen, and feeder designs	Shorter design cycle and better concept selection
Operating parameter optimization	Evaluate speed, feed rate, and clearance settings	Improved balance between cleaning efficiency and material loss
Energy optimization	Estimate energy use per processed mass	Reduced operating cost and improved sustainability
Quality preservation	Predict fiber or seed damage risk	Improved output quality
Blockage prediction	Detect high-risk operating conditions	Reduced downtime

Predictive maintenance	Monitor vibration, wear, and motor load trends	Better maintenance planning
Operator decision support	Recommend settings based on material condition	More stable equipment performance

11. Conceptual Case Study: Digital Twin for a Seed Cotton Pre-Cleaner

A conceptual case study can illustrate how the proposed framework may be applied. Consider a seed cotton pre-cleaner designed to remove foreign matter before later processing stages. The goal is to increase cleaning efficiency while limiting useful material loss and reducing energy consumption.

The digital twin receives input data describing raw material moisture, foreign matter content, feed rate, rotor speed, screen geometry, clearance settings, motor current, vibration level, and output quality. The simulation model predicts cleaning efficiency, material loss, specific energy consumption, vibration risk, and model error. The decision-support system compares different operating settings and recommends a configuration that improves overall performance.

Table 4 presents an illustrative comparison of three operating configurations. The values are conceptual and are included only to demonstrate the evaluation structure. They are not presented as measured experimental results.

Table 4. Illustrative Comparison of Operating Configurations for a Seed Cotton Pre-Cleaner

Configuration	Rotor Speed Level	Feed Rate Level	Cleaning Efficiency Score	Material Preservation Score	Energy Efficiency Score	Overall Design Score
Configuration A	Low	Medium	62	86	78	74
Configuration B	Medium	Medium	78	76	72	76
Configuration C	High	High	88	58	61	69

The comparison shows why simulation-based design is useful. The highest cleaning efficiency does not automatically produce the best overall design. Configuration C may remove more foreign matter, but it may also increase useful material loss and energy consumption. Configuration B may provide a better balance among cleaning efficiency, material preservation, and energy efficiency.

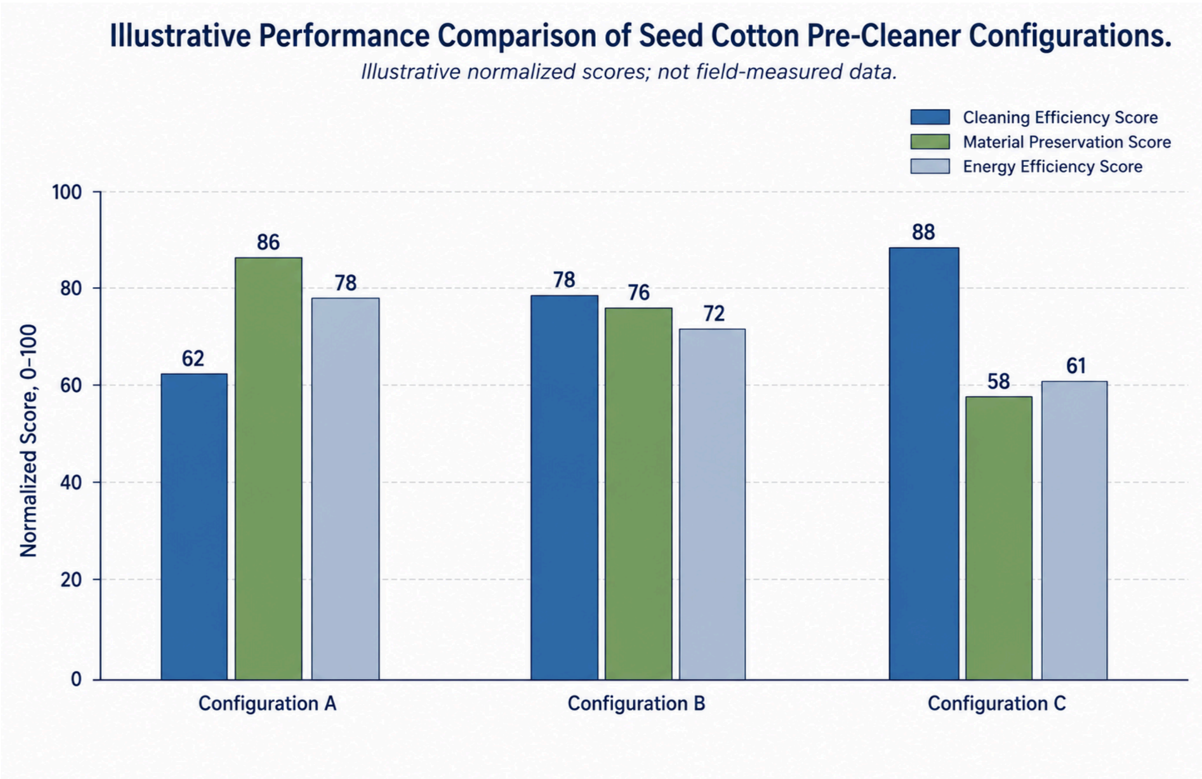

Figure 3. Illustrative Performance Comparison of Seed Cotton Pre-Cleaner Configurations

12. Design Optimization Logic

Digital twin-based optimization should not focus on a single output. A design that maximizes cleaning efficiency may damage useful material. A design that minimizes energy consumption may provide insufficient cleaning. A design that maximizes throughput may increase blockage, vibration, and wear. Therefore, agricultural processing equipment should be optimized using multiple performance indicators.

A practical optimization process may evaluate cleaning efficiency, throughput, material loss, product quality, energy consumption, vibration level, component wear, maintenance demand, and prediction error. Each indicator can be normalized and weighted according to design priorities. The resulting score can help identify balanced machine configurations.

This does not mean that the digital twin replaces engineering judgment. Instead, it provides a structured basis for comparing alternatives, identifying trade-offs, and reducing uncertainty before physical testing.

13. Integration with Predictive Maintenance

Agricultural processing equipment often operates in dusty, abrasive, and variable-load environments. These conditions can accelerate wear, cause imbalance, increase vibration, and produce unexpected downtime. A digital twin can support predictive maintenance by monitoring trends in vibration, motor current, temperature, throughput, and output quality.

If the model detects that vibration is increasing while throughput is decreasing and energy consumption is rising, the system may indicate possible wear, blockage, imbalance, or misalignment. If the digital twin observes that prediction error is increasing, it may indicate that the physical machine has changed due to wear or damage and that the model requires recalibration.

Predictive maintenance is especially important in agricultural processing because equipment downtime during harvest or processing seasons can create significant operational losses. A digital twin can help operators move from reactive maintenance to condition-based maintenance.

14. Relevance to U.S. Agricultural Manufacturing and Industrial Modernization

The proposed framework is relevant to U.S. agricultural manufacturing because agricultural processing equipment must become more efficient, data-driven, automated, and resilient. Digital twin and simulation-based design methods can support machinery modernization by reducing development time, improving energy efficiency, supporting predictive maintenance, and enabling more reliable processing under variable raw material conditions.

In the context of cotton processing, improved equipment design may support better raw material cleaning, reduced material loss, improved product quality, and more efficient integration with textile production systems. In broader agricultural manufacturing, the same framework may be applied to seed processing, grain cleaning, fiber preparation, biomass handling, and other post-harvest industrial processes.

The framework also supports the modernization of mechanical engineering practice by connecting machine design, sensor data, simulation, automation, and lifecycle performance into one integrated system.

15. Validation Requirements

A digital twin cannot be considered reliable unless it is verified and validated. Verification asks whether the model has been implemented correctly. Validation asks whether the model accurately represents the physical system for the intended purpose. This distinction is important because a mathematically correct model may still fail to represent real equipment behavior if the assumptions, parameters, or material properties are inaccurate.

For agricultural processing equipment, validation may involve comparing predicted and measured throughput, cleaning efficiency, material loss, motor current, vibration, and product quality. The model should be tested across different feed rates, raw material moisture levels, foreign matter contents, and operating speeds. The validation process should also define acceptable error limits for each performance indicator.

Sargent (2013) emphasized that simulation model verification and validation are essential for establishing model credibility. In the context of agricultural processing machinery, validation should be treated as a continuous process because raw material properties and equipment conditions may change over time.

16. Limitations

The proposed framework is conceptual and should be adapted to specific equipment types, material conditions, and industrial environments. Agricultural materials are highly variable, and their behavior may be difficult to represent using simplified models. Material flow through cleaning and separation equipment may involve complex interactions among geometry, speed, moisture, adhesion, air flow, vibration, and particle behavior.

Another limitation is data availability. Many agricultural processing facilities may not have complete sensor systems, historical datasets, or standardized product quality measurements. Digital twin implementation may therefore need to begin with a simplified model and gradually become more advanced as data become available.

Model complexity is also a practical limitation. A highly detailed simulation may be accurate but too slow for real-time decision support. A simplified model may be fast but less accurate. The correct modeling approach depends on whether the digital twin is used for early-stage design, offline optimization, operator decision support, or real-time control.

17. Future Research Directions

Future research should focus on developing digital twin models that are practical, validated, and useful for real agricultural processing environments. One important direction is the development of reduced-order models that can predict cleaning efficiency, material loss, and energy consumption quickly enough for operational decision support. Another direction is the integration of sensor systems into cotton processing and agricultural cleaning equipment so that real-time data can be used to update simulation models.

Further research may also examine machine learning models for predicting product quality, blockage risk, and maintenance needs. Digital twin models should be connected to CAD design, simulation software, control systems, and maintenance databases. In addition, future studies should develop standardized metrics for comparing digital twin performance in agricultural processing machinery.

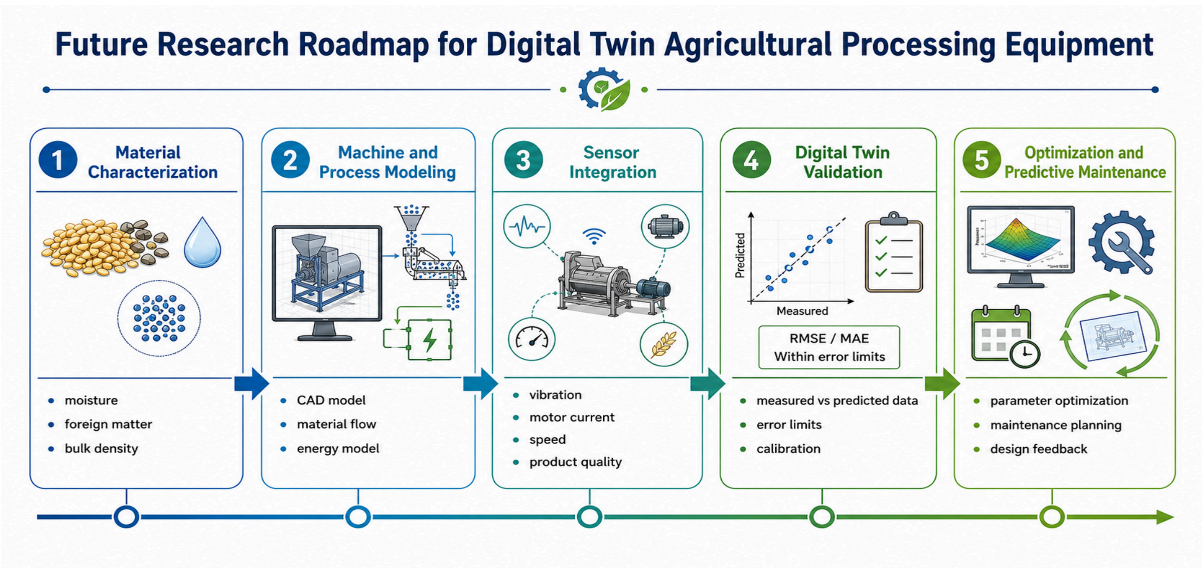

Figure 4. Future Research Roadmap for Digital Twin Agricultural Processing Equipment

18. Conclusion

Agricultural processing equipment must operate under variable raw material conditions while maintaining throughput, cleaning efficiency, product quality, energy efficiency, and mechanical reliability. Traditional design methods based mainly on physical prototyping and isolated machine adjustments may be insufficient for the next generation of data-driven agricultural machinery.

This article proposed a digital twin and simulation-based design framework for agricultural processing equipment, with emphasis on cotton cleaning, cotton separation, and raw material handling machinery. The framework integrates physical equipment, sensor data, simulation models, performance indicators, decision support, and feedback to machine design.

The proposed approach can help engineers evaluate machine configurations, optimize operating parameters, reduce material loss, improve energy efficiency, predict maintenance needs, and support sustainable agricultural manufacturing. By applying digital twin methods to agricultural processing equipment, future machinery can become more intelligent, efficient, adaptable, and aligned with modern industrial automation and manufacturing priorities.

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