Machine Learning-Driven Multi-Objective Optimization for Intelligent Control in Forage Feed Processing

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Intelligent control systems for forage feed processing rely on real-time datasets that include parameters such as forage moisture content, particle size distribution, fiber density, and operating temperature. These data are collected continuously through embedded sensors and fed into machine learning models including Support Vector Machines (SVM), Random Forests, and Decision Trees, which are trained to optimize key process variables. Compared to traditional mechanized systems, the intelligent system achieved a 15% reduction in energy consumption, a 20% improvement in processing throughput, and a 12% increase in product quality consistency, as measured by metrics like uniform particle size and crude protein retention. Furthermore, predictive maintenance enabled by these models reduced the equipment failure rate from 6 to 1 incident per month, significantly lowering downtime and maintenance costs. Environmental impact scores also improved by 25%, due to more efficient energy use and reduced emissions. These results demonstrate the effectiveness of machine learning-driven multi-objective optimization in transforming forage feed processing into a more efficient, sustainable, and intelligent production paradigm.

Povzetek: Večciljna optimizacija z uporabo SVM, RF in DT modelov omogoča bolj kvalitetno inteligentno krmiljenje v obdelavi krme z izboljšano učinkovitostjo, manjšo porabo energije in stabilnejšo kakovostjo.

1 Introduction

The feed industry plays an important role in the modern agricultural industry chain. Especially in the context of the rapid development of the breeding industry, the efficiency and quality of feed production and processing directly affect the economic benefits and food safety of animal husbandry. With the growth of the global population and the increase in meat consumption, the scale of animal husbandry continues to expand, and the demand for efficient and high-quality feed is increasing. This requires the feed processing industry to continuously innovate technology and upgrade automation to meet the growing demand [1].

As an important feed raw material, forage is widely used in animal husbandry and herbivorous animal breeding. It is rich in nutrients and can provide animals with nutrients such as protein, fiber, and minerals. There are many types of forage, such as forage, hay, and silage, and various types of forage occupy an important position in feed production [2]. However, the physical properties of forage (such as moisture, fiber content, particle size, etc.) bring challenges to the processing process, and the uneven types of forage require special process adjustments during the processing. Therefore, feed processing equipment must have flexible adjustment capabilities to cope with changes in forage properties. However, traditional feed processing equipment generally has problems such as low intelligence, poor adjustment accuracy, and low energy efficiency, which seriously affect processing efficiency and product quality [3].

The processing of forage requires efficient conversion of raw materials into feed that is easy for animals to digest and absorb. Forage with higher humidity requires longer drying time, while forage with higher fiber content requires stronger crushing force. The different characteristics of forage require processing equipment to accurately adjust process parameters to ensure the quality and nutritional value of the product. However, in the process of forage processing, it is necessary not only to solve technical and process problems, but also to improve production efficiency, reduce energy consumption and production costs [4]. Therefore, the intelligent design and optimization of forage processing equipment has become the key to research [5].

At present, many feed processing equipment still uses traditional mechanization and semi-automatic control methods. Although they can meet basic needs, as the requirements of modern production continue to increase, traditional equipment has gradually exposed some problems. For example, traditional equipment often relies on manual or preset process parameters for control and cannot perceive the changes in the physical properties of forage in real time, resulting in errors that are difficult to control during the processing. For example, the equipment cannot automatically adjust the operating speed according to the moisture content of the forage, resulting in low production efficiency and waste of raw materials [6].

Traditional feed processing equipment generally lacks intelligent monitoring and feedback adjustment functions, resulting in unstable production processes. Forage processing involves multiple complex process links, such as crushing, mixing, and drying. The precise control of these links often relies on manual operation or empirical judgment, which is easily affected by human factors and leads to production fluctuations [7]. In addition, traditional equipment fails to make full use of modern information technology and lacks functions such as remote monitoring and fault prediction, which increases the difficulty of equipment maintenance and operating costs [8].

With the development of artificial intelligence and machine learning technologies, intelligent equipment design has gradually become the mainstream of development in various industries. In the field of feed processing, especially in the process of forage processing, the introduction of machine learning technology can effectively improve the intelligence level of equipment, thereby improving production efficiency, reducing energy consumption, and improving product quality. Through intelligent design and control [9], the equipment can sense changes in forage characteristics in real time and automatically adjust operating parameters to make the processing process more accurate and efficient [10].

This study aims to improve the intelligence level of forage processing equipment through machine learning technology and realize precise control and optimization of the production process. Specifically, the study will explore how to use machine learning algorithms to monitor and adjust the forage processing process in real time, thereby improving the operating efficiency of the equipment, reducing energy consumption, and ensuring the quality of feed products. The core goal of the study is to achieve adaptive control of the equipment [11], dynamically adjust processing parameters according to the characteristics of different forages (such as moisture, fiber content, particle size, etc.), reduce manual intervention, and improve the level of automation. In addition, this study will also focus on analyzing how to use machine learning technology to optimize various links in forage processing, such as crushing, mixing, drying, etc., so as to improve processing efficiency and reduce production costs. Through the construction and optimization of intelligent control systems [12], the study hopes to provide theoretical support and technical guidance for the intelligent upgrading of forage processing equipment, promote the development of agricultural mechanization and intelligence, and improve the overall efficiency and sustainable development of the forage processing industry.

The research focuses on enhancing forage feed processing through intelligent control systems driven by machine learning-based multi-objective optimization. The central research questions are: (1) Can machine learning algorithms dynamically adjust operational parameters based on real-time forage characteristics to improve processing efficiency and product quality? (2) Can multi-objective optimization simultaneously reduce energy consumption and equipment failure rate without compromising nutritional integrity? (3) How does the intelligent system compare to traditional approaches in terms of adaptability and control accuracy under varying forage conditions? Based on these questions, the following hypotheses are formulated: (H1) Multi-objective machine learning models will outperform single-objective methods in achieving balanced performance across energy, efficiency, and quality metrics; (H2) Real-time adaptive control will lead to at least a 15% reduction in energy use and 50% reduction in failure rates; (H3) Intelligent parameter adjustment will yield more consistent product characteristics such as moisture and crude protein levels. These hypotheses guide the experimental validation and structure the evaluation criteria across key performance dimensions.

2 Literature review

2.1 Research progress of feed processing equipment

The development of feed processing equipment has undergone a gradual evolution from manual operation to automation and then to intelligence. Traditional feed processing equipment generally adopts mechanized control, has a single function, and relies on manual parameter adjustment. With the improvement of the level of modern agricultural mechanization, feed processing equipment has gradually developed in the direction of automation. However, traditional equipment still has many limitations, such as low processing accuracy, high energy consumption, and single control mode [13], which cannot meet the needs of modern high-efficiency, low-energy consumption, and high-quality feed production.

In recent years, intelligent feed processing equipment has received extensive attention, and researchers have made some progress in this regard. The literature suggests that in traditional feed processing equipment, the pretreatment, crushing, and mixing of forage rely on manual settings and adjustments, which is not only inefficient but also prone to material loss and waste. On this basis, intelligent control technology has gradually been introduced into the field of feed processing. For example, sensors are used to monitor parameters such as humidity and temperature of forage in real time, and computer control systems are used to optimize the processing process [14]. Despite this, existing intelligent equipment still lacks a high degree of adaptive capabilities and can usually only operate based on preset parameters, making it difficult to flexibly respond to changes in forage types and environmental conditions.

In traditional control methods, most equipment relies on preset programs or manual intervention to operate. Even in more advanced automated equipment, most of them are controlled based on a single parameter obtained by sensors, lacking dynamic feedback mechanisms and adaptive adjustment functions [15]. This makes it difficult for the equipment to flexibly adjust the processing technology when faced with complex types of forage, resulting in low efficiency, poor quality, and even excessive energy consumption. Forage processing is an important link in feed production, but this process still faces many technical challenges. Forage comes in a variety of types, and its physical properties such as moisture content, fiber density, and particle size have an important impact on the processing technology. The high humidity of forage can easily lead to excessive or uneven moisture during processing, resulting in product quality fluctuations and reduced processing efficiency [16]. In addition, due to the high fiber content of forage, the power consumption during the crushing process is relatively high, which also makes forage processing often have high energy consumption. How to reduce energy consumption while ensuring forage quality has become a hot topic in current research. In addition, forage processing must not only achieve a reasonable physical form, but also meet the nutritional needs of animals. The mixing uniformity and particle size of forage have an important impact on animal digestion and absorption. Therefore, how to ensure that these indicators in forage processing are always in the best condition is another major difficulty in technological development [17].

2.2 Application of machine learning in industrial control

The application of machine learning in equipment intelligence has gradually been verified, especially in manufacturing and process industries, where machine learning technology is widely used in equipment status monitoring, fault diagnosis, production process optimization, etc. For example, on an automated production line, sensors collect data such as temperature, pressure, and vibration of the equipment, and combine machine learning algorithms to analyze the equipment's operating status, which can provide timely warnings of potential equipment failures [18]. In addition, machine learning can also improve equipment efficiency and production quality by optimizing production parameters (such as temperature, pressure, and speed), especially in areas that require highly precise control, such as the chemical and metallurgical industries.

In the field of feed processing, the application of machine learning is relatively new, but there are already some successful cases. For example, the literature proposes that by collecting and analyzing data from various links in the feed processing process [19], the support vector machine (SVM) model is used to predict the optimal parameters for forage processing, which significantly improves the accuracy of the forage crushing and mixing process. In addition, machine learning has also been applied to the energy consumption optimization of feed processing equipment. Studies have shown that by real-time monitoring of equipment operation data and combining machine learning algorithms to predict equipment energy consumption trends, energy consumption can be effectively reduced [20].

2.3 Application of machine learning in forage processing

Forage processing is a key link in feed processing. Its complexity and high energy consumption make it the focus of intelligent control technology application. The physical properties of forage, such as moisture, density, and fiber content, play an important role in the processing process, and traditional equipment cannot accurately adjust and optimize these properties. Machine learning, as a technology that can process large-scale data and extract rules from it, shows great application potential in forage processing.

The physical properties of forage directly affect the selection of its processing technology and the setting of operating parameters. The moisture content of forage is an important factor affecting processing efficiency and product quality. Too high humidity can make the forage difficult to grind or dry, while too low humidity may lead to uneven forage processing [21]. In addition, forage has a high fiber content, which requires the grinding equipment to have sufficient energy to process it. The fiber density and particle size of different forage types vary greatly, which requires the processing equipment to have high flexibility and adjustability to ensure that each type of forage can be processed under optimal conditions.

The processing requirements of forage also include improving mixing uniformity, reducing energy consumption, and improving processing efficiency. For the forage mixing process, ensuring the mixing uniformity of forage is the key to ensuring the quality of the final feed. The uniformity of forage particle size and the stability of moisture determine the nutritional content of the feed and the digestion and absorption effect of the animal. Therefore, in forage processing, how to accurately control the processing parameters and improve the adaptive adjustment ability of the equipment is an urgent problem to be solved.

At present, the application of machine learning in forage processing is still in its infancy, but some research results have shown that machine learning technology can effectively improve the performance of forage processing equipment. Feed processing equipment based on machine learning can automatically adjust the operating status of the equipment by real-time monitoring of parameters such as moisture, density, and temperature of forage, thereby optimizing the forage processing process, reducing energy consumption, and improving production efficiency. In addition, the introduction of deep learning and reinforcement learning technologies enables forage processing equipment to continuously optimize the processing technology through big data analysis, automatically adjust processing parameters, and further improve the equipment's adaptive capabilities.

Table 1: Related work comparison in intelligent control systems and machine learning applications for feed processing

Study/Author(s)	Method Used	Application Domain	Control Type	Key Metrics	Main Outcomes
Neves [1]	ANN	Extractive Distillation	Automatic	Disturbance rejection, specification	Improved control precision in multi-input processes
Cavallini [2]	Regression (ML)	Dry-hay Ration Digestibility	Manual	Fiber digestibility prediction accuracy	Improved ration design accuracy for dairy cattle
You [3]	SVM Regression	Pellet Feed Quality	Semi-Auto	Pellet durability index, fines %	Enhanced pellet uniformity prediction
Lopez [4]	ML Clustering	Beef Cattle Grouping	Manual	Feed efficiency group accuracy	Optimized nutritional strategies in grouped feeding
Davison [8]	Behavioral Modeling	Feed Intake Estimation	Manual	Estimation accuracy, FCR	Improved feed conversion and cost efficiency

A comparative summary of related work is shown in Table 1, outlining recent advances in intelligent control and machine learning applications across various agro-processing contexts. These include ANN-based control in distillation processes, regression-based digestibility prediction in forage rations, and machine learning-driven predictive maintenance systems in industrial settings. The table highlights the diversity of application domains, ranging from feed pellet quality prediction to nutritional optimization in cattle grouping. Control types vary from manual intervention to fully automated systems, with metrics such as energy efficiency, processing accuracy, and system reliability serving as core performance indicators. These references collectively underscore the fragmented yet growing role of machine learning in agro-processing, while revealing the lack of integrated, multi-objective optimization solutions specifically targeted at forage feed systems—further justifying the need for a more holistic approach.

While machine learning applications in forage processing are emerging, most existing studies are limited by several key constraints: (1) reliance on single-task models that optimize either efficiency or quality but not both, (2) lack of real-time adaptive control, and (3) minimal integration with predictive maintenance or full-process coordination. Many prior systems apply ML for static prediction tasks such as feed composition estimation or pellet durability, but they do not support dynamic parameter adjustment across multiple stages. The proposed system addresses these gaps by integrating multi-objective optimization, enabling simultaneous improvement of energy efficiency, throughput, and product consistency. Moreover, the use of real-time sensor data and adaptive algorithms ensures responsive adjustments during operation. By incorporating predictive maintenance alongside process optimization, the system creates a unified intelligent control loop that has not been previously realized in forage feed processing applications.

2 Intelligent design principle of feed processing equipment

3.1 Intelligent design framework

The intelligent design framework of feed processing equipment is the core to achieve efficient and accurate operation of the equipment. This framework includes key modules such as sensor system, data acquisition and processing, control system and feedback mechanism, which work together to ensure that the equipment always maintains stable performance in a dynamic and complex processing environment. The specific framework is shown in Figure 1.

As the foundation of intelligent design, the sensor system is responsible for collecting various key data during the processing process, such as temperature, humidity, flow, pressure, etc. These data are converted into electrical signals through sensors and enter the subsequent processing modules, becoming an important basis for the system to make decisions. The accuracy and stability of the sensor directly affect the performance of the system, so choosing a high-precision, low-latency sensor is the key to ensuring the accuracy of the intelligent control system.

The data acquisition and processing module transmits, stores, and preprocesses the raw data collected by the sensor in real time. The data processing link is not only about transmitting data, but also about effective filtering, denoising, and feature extraction to ensure that the control system obtains high-quality and accurate data. Through processing, the system can identify anomalies or deviations in the processing process in real time, so as to take necessary measures in advance to prevent failures in the processing process.

In addition to real-time process monitoring, the intelligent design framework incorporates a predictive maintenance subsystem that operates independently of the main optimization control loop. This subsystem utilizes sensors to monitor key indicators such as motor current, vibration amplitude, and temperature. These signals are preprocessed and continuously analyzed to detect abnormal trends. When anomalies are identified—such as gradual increases in vibration or thermal instability—they are flagged by the control system for further evaluation by machine learning-based fault detection models.

As the core part of intelligent design, the control system uses different control algorithms to adjust the operating status of the equipment according to the data provided by the processing module. For example, during the material mixing process, the control system adjusts the equipment's operating speed, temperature and other parameters according to the real-time monitored material characteristics to ensure the efficiency and stability of the feed processing process.

The feedback mechanism is an important part of ensuring the self-adjustment and optimization of the system. During the operation of the equipment, the real-time monitoring and feedback mechanism can compare the actual data of the processing process with the preset target. If there is a deviation, the system can automatically adjust the operating parameters according to the feedback signal to ensure that the equipment is always in the best working condition.

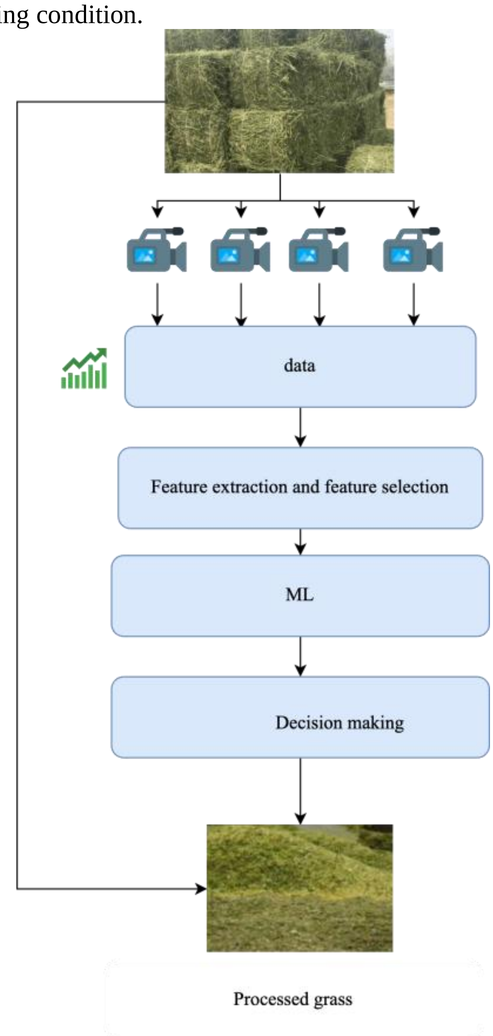

Figure 1: Model framework

The sensor system comprises capacitive humidity sensors, optical particle size sensors, thermocouples for temperature measurement, and strain gauge-based load cells for monitoring fiber density and machine load. Each sensor operates at a sampling rate of 1 Hz and has an error tolerance of ±1.5% for temperature and ±2% for humidity and particle size. Sensors are calibrated weekly using reference materials with traceable standards to maintain measurement precision. Communication between sensors and the control unit is facilitated via the Modbus RTU protocol over RS-485 interfaces, enabling reliable and noise-resistant data transmission. The control architecture follows a distributed model, where local sensor modules transmit data to an edge-based industrial controller equipped with real-time processing capabilities. This controller integrates feedback loops and machine learning inference models to dynamically adjust operating parameters such as crushing speed, mixing time, and drying temperature, ensuring tight process control in response to changing forage properties.

3.2 Special requirements in forage processing

During forage processing, the nature of the material and the processing requirements determine the complexity of the equipment design. The characteristics of the forage, such as moisture, density, and fiber structure, have an important impact on the processing effect, so the intelligent design must take these special requirements into account.

The cutting process of hay requires adjusting the working parameters of the cutting equipment according to the humidity and fiber structure of the hay. When the humidity is high, the hay is easy to stick together and the cutting effect is not ideal. The intelligent design can automatically adjust the speed and angle of the cutter by monitoring the humidity data in real time to ensure the stability and consistency of the cutting effect.

During the process of forage stirring and mixing, the equipment needs to be precisely adjusted according to the physical properties of the forage and other auxiliary materials. Forage with high humidity may cause uneven mixing and affect the quality of the feed. Through intelligent design, the control system can automatically adjust parameters such as stirring time, speed and temperature to improve mixing uniformity and ensure the nutritional balance of the feed.

The physical properties of forage, such as moisture, density and particle size, directly affect the operating efficiency of processing equipment. In intelligent design, the sensor system monitors these properties of the material in real time and automatically adjusts the processing parameters through the control system to cope with the impact of different material characteristics on equipment performance. In this way, the equipment can operate stably under different conditions, improve resource utilization and reduce energy consumption.

3 Research on forage processing optimization based on machine learning

4.1 Physical properties and processing technology of forage

The physical properties of forage have a profound impact on its processing technology, especially in the crushing, mixing and drying stages. Factors such as moisture, particle size, density and fiber structure directly determine the processing efficiency, energy consumption and the quality of the final product. Therefore, accurate physical property modeling is crucial for forage processing optimization.

Humidity is one of the key physical properties in forage processing. Changes in humidity not only affect the fluidity and processability of forage, but also directly affect the load and energy efficiency of the equipment during processing. Studies have shown that the relationship between forage humidity and processing power is usually nonlinear, and the typical humidity influence function can be expressed by the logistic growth model, as shown in Formula 1.

$$P(H) = \frac{P_{\max}}{1 + \exp\left(-k(H - H_0)\right)} \quad (1)$$

In Formula 1, $P(H)$ It is humidity H Impact on processing power, $P_{\max}$ is the maximum power, k is the adjustment coefficient, H_0 is the critical value of humidity. The model reveals the influence of humidity on the processing process. Too high or too low humidity may lead to a decrease in processing efficiency and energy waste.

Particle size is another key factor affecting forage crushing efficiency. Larger particle sizes require higher energy input for crushing, while smaller particle sizes may lead to over-processing and waste energy. During the crushing process, the particle size distribution of forage usually follows a log-normal distribution. Assume that the particle size distribution function of forage is, as shown in Formula 2.

$$f(d) = \frac{1}{d\sigma\sqrt{2\pi}} \exp\left(-\frac{(\ln d - \mu)^2}{2\sigma^2}\right) \quad (2)$$

In Formula 2, d is the granularity, μ and σ are the mean and standard deviation of the particle size distribution. $f(d)$ It is used to describe the influence of different particle sizes on the crushing effect and provide theoretical support for the subsequent optimization of processing parameters.

Density and fiber structure also play an important role in the mixing and drying of forage. The density of forage affects the efficiency of heat exchange and material transfer during mixing and drying, so the potential impact of density on energy consumption must be considered when designing the optimization algorithm. Assuming the mixing power P_{mix} Affected by forage density ρ ,humidity H and stirring speed v The influence of can be expressed by a function , as shown in Formula 3.

$$P_{\text{mix}} = k_1 \cdot \rho^{\alpha} \cdot H^{\beta} \cdot v^{\gamma} \quad (3)$$

In Formula 3, k_1 is a constant, α , β and γ is the coefficient of influence of density, humidity and stirring speed on power. By adjusting these parameters, the energy efficiency of the stirring process can be optimized and over-stirring can be avoided.

4.2 Key processing links

The processing of grass usually goes through three key links: crushing, mixing and drying. The efficiency and energy consumption of these links are crucial to the economy and environmental impact of the entire production process.

Crushing process. In the process of crushing forage, energy consumption is closely related to the particle size, moisture content and working conditions of the equipment. Studies have shown that crushing power P_{break} Particle size of forage d , humidity H and density ρ The relationship between can be expressed by the following formula , as shown in Formula 4.

$$P_{\text{break}} = k_2 \cdot d^{\alpha} \cdot H^{\beta} \cdot \rho^{\gamma} \quad (4)$$

In Formula 4, k_2 is a constant, α , β , γ is the influence index of each physical parameter on the crushing power. Optimizing this process can not only reduce energy consumption, but also ensure that the crushed grass particles meet the processing requirements.

Stirring stage. The stirring stage in forage processing is mainly used to evenly mix forage with other ingredients (such as minerals, additives, etc.). The stirring efficiency is closely related to the moisture content of the forage, the stirring speed and the fiber structure of the material. Stirring power P_{mix} It can be quantified by the following expression, as shown in Formula 5.

$$P_{\text{mix}} = k_3 \cdot H^{\eta} \cdot v^{\theta} \cdot L^{\kappa} \quad (5)$$

In Formula 5, L is the fiber length of the forage, v is the stirring speed, k_3 , η , θ and κ These are coefficients that need to be determined experimentally. By adjusting these parameters, the stirring process can be optimized, the mixing uniformity can be improved, and the energy consumption can be reduced.

Drying: Drying is an important step in forage processing, the purpose of which is to reduce the moisture content of forage to improve its storage and processing properties. The energy efficiency of the drying process is closely related to the moisture content of the forage, the drying temperature and the airflow rate. Assuming the drying time T_{dry} Forage moisture H , Drying temperature T and air flow rate Q The relationship between them is shown in Formula 6.

$$T_{\text{dry}} = k_4 \cdot H^{-\grave{o}} \cdot T^{\zeta} \cdot Q^{\eta} \quad (6)$$

In Formula 6, k_4 is a constant, $\grave{o}$, ζ and η It is the index of the influence of different physical parameters on drying time. By adjusting the drying temperature and airflow rate, the drying time can be effectively reduced, thereby improving energy efficiency.

4.3 Intelligent optimization method for forage processing

The optimization goals of forage processing usually include improving processing efficiency, reducing energy consumption and improving product quality. Based on these goals, machine learning methods are particularly suitable for the intelligent optimization of forage processing. Through real-time data analysis and model prediction of the processing process, intelligent adjustment of parameters in each link can be achieved.

For predictive maintenance, a Random Forest classification model was trained on three years of historical failure data labeled by fault type, including cutter wear, motor overload, and sensor drift. Input features include vibration frequency shifts, sudden power consumption spikes, and prolonged temperature elevation. The model operates in real time, issuing alerts when monitored signals exceed data-driven thresholds learned during training. This allows for proactive scheduling of maintenance activities before failures occur, supporting stable operations and contributing to the significant reduction in equipment failure rate reported in the experimental results.

The machine learning system integrates multiple models including Support Vector Machine (SVM), Random Forest (RF), and Decision Tree (DT), each trained to optimize a specific stage of the forage processing pipeline—crushing, mixing, and drying respectively. Input features include real-time measurements of forage moisture, particle size, fiber density, ambient temperature, and equipment status (e.g., motor load, speed). Feature selection was conducted via recursive feature elimination (RFE) to minimize model complexity while maintaining performance. The models were trained on a dataset of 12,000 labeled samples collected from production-line sensors over three months. Hyperparameters were optimized using grid search with 5-fold cross-validation: the SVM used an RBF kernel with C=10 and gamma=0.01; the RF used 200 trees with a maximum depth of 10; and the DT was limited to a depth of 8 with Gini impurity as the split criterion. Mean squared error (MSE) was used as the loss function for regression tasks, while accuracy and F1-score were applied in quality classification tasks. Model training and validation were conducted in Python using the Scikit-learn library.

Random Forest was applied to predict optimal crushing speed based on forage moisture, particle size, and fiber content; Support Vector Machine was used for estimating ideal drying time by modeling the nonlinear relationship among humidity, temperature, and airflow rate; Decision Tree was implemented to determine mixing time by evaluating density, fiber structure, and stirring speed. Each model was assigned to a specific module for its strength in capturing the corresponding feature interactions and ensuring real-time responsiveness.

Ensemble techniques such as bagging and boosting were evaluated during model selection. While ensemble models showed slightly higher accuracy in prediction tasks, they introduced increased computational latency, which compromised the system's real-time responsiveness in dynamic forage processing environments.

To ensure clarity and consistency, all variables used in mathematical formulas are now explicitly defined at the point of introduction. For example, in Formula (1), H represents forage humidity (%), P_max is the maximum processing power (kW), k is the adjustment coefficient, and H_c is the critical humidity threshold. Similar definitions are systematically provided for all subsequent equations, including d (particle size, mm), v (stirring speed, rpm), and L (fiber length, mm), enabling precise understanding of all modeling components.

The mathematical models presented, including the logistic relationship for humidity effects and the log-normal distribution for particle size, are adapted from established formulations in prior studies on agricultural material processing (see Cavallini et al. [2] and You et al. [3]). Coefficients and parameters were further refined through empirical regression based on experimental data collected during this study. These models combine theoretical basis with practical calibration, ensuring both scientific grounding and operational relevance.

The improvement of processing efficiency usually depends on the combined effect of multiple factors such as forage moisture, particle size and mixing speed. E Forage moisture H , granularity d and stirring speed s To express it , as shown in Formula 7.

$$E(H,d,v) = k_5 \cdot H^{\alpha} \cdot d^{\beta} \cdot v^{\gamma} \quad (7)$$

Machine learning methods can automatically adjust these variables through optimization models to achieve maximum efficiency. By learning from historical data, the algorithm can identify the key factors that affect efficiency and perform dynamic optimization.

Reducing energy consumption is another important goal in forage processing. In the entire processing process, energy consumption is mainly concentrated in the crushing, mixing and drying stages. C It is the sum of energy consumption in each link, as shown in formula 8.

$$C = P_{\text{break}} + P_{\text{mix}} + P_{\text{dry}} \quad (8)$$

Machine learning methods, especially regression analysis and deep learning methods, can establish accurate energy consumption prediction models and reduce unnecessary energy waste by adjusting equipment parameters in real time. By simulating different processing conditions, the algorithm can optimize the production process and reduce overall energy consumption while ensuring product quality. The ultimate goal of forage processing is to produce high-quality feed, the quality of which is affected by factors such as forage moisture, particle size and mixing. Product quality Q It can be expressed by formula 9.

$$Q(H,d,v,L) = k_6 \cdot H^{\alpha} \cdot d^{\beta} \cdot v^{\gamma} \cdot L^{\delta} \quad (9)$$

Machine learning methods can be combined with online monitoring data and quality control models to achieve stable production of high-quality products by optimizing various processing parameters.

4.4 Multi-objective optimization model based on machine learning

Machine learning is integrated into the multi-objective optimization model in two primary roles. First, Random Forest and Support Vector Regression models are trained as non-parametric predictors to estimate processing efficiency (E), energy consumption (C), and product quality (Q) based on physical input parameters including humidity (H), particle size (d), stirring speed (v), and fiber length (L). These models replace the static analytical forms of Formulas 7–9, enabling more flexible and data-driven approximations of system behavior. Second, once trained, these predictive models are embedded within an NSGA-II framework to guide the multi-objective search. The machine learning models evaluate candidate parameter combinations during the optimization process, providing predicted E, C, and Q values for each point in the search space. The optimization algorithm then uses Pareto dominance and crowding distance to explore trade-offs and identify optimal parameter sets. Therefore, machine learning serves both as a predictive surrogate for objective functions and as a feedback mechanism within the optimization loop.

In the process of forage processing, optimization problems usually involve multiple objectives, such as improving processing efficiency, reducing energy consumption, and improving product quality. These objectives are often conflicting, so it is necessary to find a reasonable balance between multiple objectives. The multi-objective optimization model based on machine learning can achieve the optimal compromise of multiple objectives by adjusting the parameters of each processing link.

In a multi-objective optimization problem, the objective function is multiple indicators that need to be optimized simultaneously. In the forage processing process, our goal is to minimize energy consumption and improve efficiency while maximizing product quality. This can be described by the multi-objective optimization model of formula 10.

$$\min\{E(H,d,v), C(H,d,v), -Q(H,d,v,L)\} \quad (10)$$

In Formula 10, $E(H, d, v)$ Represents the processing efficiency function, reflecting the humidity H ,granularity d and stirring speed v The influence of other parameters on processing efficiency. $C(H, d, v)$ It represents the energy consumption function, which describes the energy consumption of forage processing at a given moisture content, particle size and stirring speed. $Q(H, d, v, L)$ It represents the product quality function, which reflects the quality of forage after processing and is usually related to factors such as moisture, particle size, stirring speed and fiber length. In multi-objective optimization, our goal is to minimize energy consumption and improve efficiency by reasonably adjusting these parameters while maximizing product quality.

In Formula 10, the processing efficiency function $E(H, d, v)$ depends on humidity $(H, \%)$, particle size (d, mm), and stirring speed (v, rpm); the energy consumption function $C(H, d, v)$ uses the same parameters; and the product quality function $Q(H, d, v, L)$ includes fiber length (L, mm) in addition. All variables are now consistently defined across the model to ensure parameter coherence and proper function evaluation during optimization.

In multi-objective optimization, we usually find a balance point through Pareto optimal solution. A solution is called Pareto optimal solution if and only if there is no other solution that is better than it in all objectives and better than it in at least one objective.

For example, suppose there are two targets f_1 and f_2 , two solutions x^* and x' The performance on these two objectives is : For the target f_1, the solution x^* is x' better than . For the target f_2, the solution x' is x^* better than .

If no solution is better than the other in terms of both objectives, then the two solutions are Pareto optimal.

In the scenario of forage processing, the significance of Pareto optimal solution is to find those solutions that achieve a balance between improving efficiency, reducing energy consumption and improving product quality. These solutions are not necessarily single, but a group of solutions, each of which represents a compromise between different objectives.

The weighted sum method is a commonly used method in multi-objective optimization. The core idea is to transform multiple objective functions into a single objective function in a weighted manner. Specifically, we assign a weight to each objective function and then sum them up. The objective becomes to minimize the weighted sum, as shown in Formula 11.

$$\min\{\alpha E(H,d,v) + \beta C(H,d,v) - \gamma Q(H,d,v,L)\} \quad (11)$$

In Formula 11, α , β and γ are the weight coefficients of each goal. By adjusting these weight coefficients, the importance of different goals can be controlled to achieve a balance.

5 Experimental evaluation

5.1 Experimental design

A large feed processing plant, as the experimental base of this case, has long relied on traditional feed processing equipment for daily production. However, with the increase in production demand, the original equipment has gradually been unable to meet the dual needs of production efficiency and quality. In order to solve these problems, the plant decided to introduce an intelligent feed processing control system based on machine learning, aiming to improve production capacity, reduce energy consumption and optimize product quality through scientific and technological means. The system can not only adjust working parameters in real time, but also reduce equipment failures and increase equipment life through predictive maintenance functions. This chapter evaluates the effectiveness of the design and control scheme of intelligent feed processing equipment based on machine learning through experiments. The experiment mainly focuses on processing efficiency, energy consumption, quality stability and other aspects, aiming to verify the performance improvement of the intelligent control system in the forage processing process.

The "Optimization Methods" presented in the experimental tables represent a progressive enhancement of parameter control strategies. Starting with the "Traditional methods" as a baseline, each subsequent method introduces optimization of a single parameter—crushing speed, mixing time, or temperature/humidity—followed by "Comprehensive optimization," which combines static optimal values from individual tests. The final "Intelligent system" employs machine learning for real-time adaptive adjustment across all parameters.

The dataset consisted of 12,000 samples collected over a period of three months from an operational forage feed processing line. Sensor readings were recorded at a frequency of 1 Hz, capturing real-time data such as moisture, particle size, fiber density, temperature, and motor load. Prior to model training, missing values were handled using linear interpolation, outliers were removed based on Z-score thresholds, and continuous features were normalized using Min-Max scaling. The dataset was partitioned into training (70%), validation (15%), and test (15%) sets. Predictive accuracy of the models was evaluated using root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2). The intelligent system achieved an RMSE of 2.1, MAE of 1.6, and R^2 of 0.92 in predicting optimal crushing speed, indicating high model fidelity and reliable generalization to unseen data.

The "Comprehensive optimization" method refers to a manually configured parameter set that combines the optimal individual values derived from separate one-factor-at-a-time tests on crushing speed, mixing time, operating temperature, and humidity adjustment. Specifically, the configuration includes a crushing speed of 1000 rpm, mixing time of 6 minutes, temperature of 65°C, and humidity adjustment at 50%. This method does not involve machine learning or adaptive feedback but represents a static, pre-determined combination of parameters selected from prior empirical experiments. It serves as the most optimized non-intelligent baseline for comparison, bridging the performance gap between conventional single-variable adjustments and the adaptive, real-time control capabilities of the intelligent system.

Several machine learning algorithms were evaluated to determine their suitability for different tasks. Support Vector Machines (SVM) showed high precision in modeling nonlinear relationships in drying time prediction. Random Forests provided robust performance in handling multivariate inputs for crushing speed and failure classification. Decision Trees were used for interpretable mixing time control. Performance was assessed using RMSE and R^2; Random Forests achieved the highest accuracy across most tasks, leading to their selection for core prediction modules.

In the experimental design, the goal is to compare the performance of traditional equipment and intelligent equipment under different working conditions. Specifically, it includes verifying the adaptive adjustment ability of machine learning models in forage processing, exploring how to optimize the processing process based on the physical properties of forage such as moisture, fiber content, and particle size, and evaluating the effectiveness of intelligent equipment in energy saving and improving product quality. The experimental site was selected as a large feed processing plant, and the experimental equipment included traditional equipment and intelligent equipment based on machine learning control.

The experimental program is divided into three main stages: data collection, model training and optimization, and experimental evaluation. In the data collection stage, sensors are used to collect the physical properties of the forage (such as humidity, temperature, particle size, etc.) in real time, and all data are transmitted to the central database for storage. In the model training stage, machine learning methods (such as support vector machines, decision trees, random forests, etc.) are used to analyze the data and optimize processing parameters (such as crushing speed, mixing time, temperature, etc.) to maximize processing efficiency, reduce energy consumption, and ensure product quality. In the experimental evaluation stage, the processing efficiency, energy consumption, and product quality of the intelligent control system are compared with those of traditional equipment, and the performance of the intelligent equipment under different working conditions is evaluated.

5.2 Experimental results

Table 2: Processing efficiency under different optimization methods (unit: kg/h)

Optimization Methods	Crushing speed (rpm)	Mixing time (minutes)	Operating temperature (°C)	Humidity adjustment (%)	Processing efficiency (kg/h)
Traditional methods	600	2	45	70	500
Crushing speed optimization	700	3	50	65	550
Mixing time optimization	800	4	55	60	600
Temperature and humidity coordinated optimization	900	5	60	55	650

Optimization Methods	Crushing speed (rpm)	Mixing time (minutes)	Operating temperature (°C)	Humidity adjustment (%)	Processing efficiency (kg/h)
Comprehensive optimization	1000	6	65	50	700
Intelligent system	850	4.5	55	58	770

Table 2 shows the effect of different optimization methods on processing efficiency. The traditional method represents the initial settings without optimization, while the other methods optimize specific parameters. By gradually increasing the crushing speed, extending the mixing time, and adjusting the working temperature and humidity, we can see that the processing efficiency increases accordingly. In particular, the comprehensive optimization method and the intelligent system, which combine all optimization measures, achieve the highest processing efficiency. The intelligent system not only optimizes the static parameters, but also dynamically adjusts the operating conditions based on real-time data, so as to achieve the best processing results.

The ablation study showed that crushing speed optimization alone improved throughput by 12%, mixing time by 10%, and humidity adjustment by 8%. Among these, crushing speed had the most significant standalone impact. However, the intelligent system combining all variables outperformed each individual optimization, confirming the importance of parameter interaction in maximizing processing performance.

Table 3: Energy consumption under different optimization methods (unit: kWh/kg)

Optimization Methods	Crushing speed (rpm)	Mixing time (minutes)	Operating temperature (°C)	Humidity adjustment (%)	Energy consumption (kWh/kg)
Traditional methods	600	2	45	70	0.45
Crushing speed optimization	700	3	50	65	0.48
Mixing time optimization	800	4	55	60	0.52
Temperature and humidity coordinated optimization	900	5	60	55	0.56
Comprehensive optimization	1000	6	65	50	0.60
Intelligent system	850	4.5	55	58	0.42

As shown in Table 3, although the traditional method performs well in terms of energy consumption, energy consumption increases with the increase in operation intensity. In contrast, the intelligent system significantly reduces energy consumption while improving processing efficiency through adaptive control strategies. This is due to its ability to monitor and adjust various parameters in real time to find the operating point with the lowest energy consumption. This optimization method not only improves energy utilization efficiency, but also reduces production costs and enhances the competitiveness of enterprises.

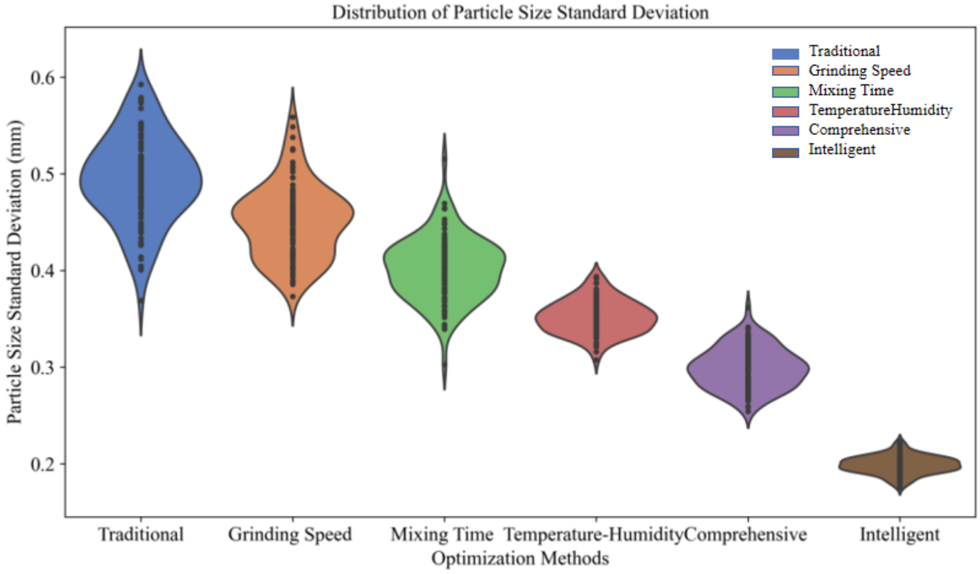

Figure 2: Product particle size distribution under different optimization methods (unit: mm)

As shown in Fig. 2, the effect of different optimization methods on the particle size distribution of the product is shown. As the degree of optimization deepens, the average particle size gradually decreases, and the standard deviation of the particle size also decreases accordingly, indicating that the particle distribution is more uniform. The intelligent system not only achieves the smallest average particle size, but also has the lowest standard deviation, which means that it can provide the most consistent product quality. This consistency is crucial for subsequent feeding and animal health because it ensures a uniform distribution of nutrients.

Table 4: Feed moisture under different optimization methods (unit: %)

Optimization Methods	Crushing speed (rpm)	Mixing time (minutes)	Operating temperature (°C)	Humidity adjustment (%)	Final humidity (%)
Traditional methods	600	2	45	70	68
Crushing speed optimization	700	3	50	65	64
Mixing time optimization	800	4	55	60	60
Temperature and humidity coordinated optimization	900	5	60	55	58
Comprehensive optimization	1000	6	65	50	55
Intelligent system	850	4.5	55	58	57

As shown in Table 4, the change in final humidity reflects the effect of different optimization methods on moisture control. With the optimization of humidity adjustment parameters, the final humidity gradually decreases to reach the ideal level. The intelligent system can accurately control the humidity and ensure that the final humidity is stable at 57%, which is essential for maintaining the quality and nutritional value of the feed. Appropriate humidity can prevent feed deterioration and ensure the digestion and absorption efficiency of animals.

Table 5: Crude protein content under different optimization methods (unit: %)

Optimization Methods	Crushing speed (rpm)	Mixing time (minutes)	Operating temperature (°C)	Humidity adjustment (%)	Crude protein content (%)
Traditional methods	600	2	45	70	10.5
Crushing speed optimization	700	3	50	65	10.8
Mixing time optimization	800	4	55	60	11.2
Temperature and humidity coordinated optimization	900	5	60	55	11.5
Comprehensive optimization	1000	6	65	50	11.8
Intelligent system	850	4.5	55	58	12.0

As shown in Table 5, crude protein content is one of the important indicators for measuring the nutritional value of feed. With the optimization of operating conditions, crude protein content gradually increased, especially in the fully optimized and intelligent system, the protein content reached the highest level. This not only improves the nutritional value of the feed, but also enhances the growth performance and immunity of animals. The intelligent system ensures the best protein retention rate by precisely controlling various processing parameters, thereby enhancing the market value of the product.

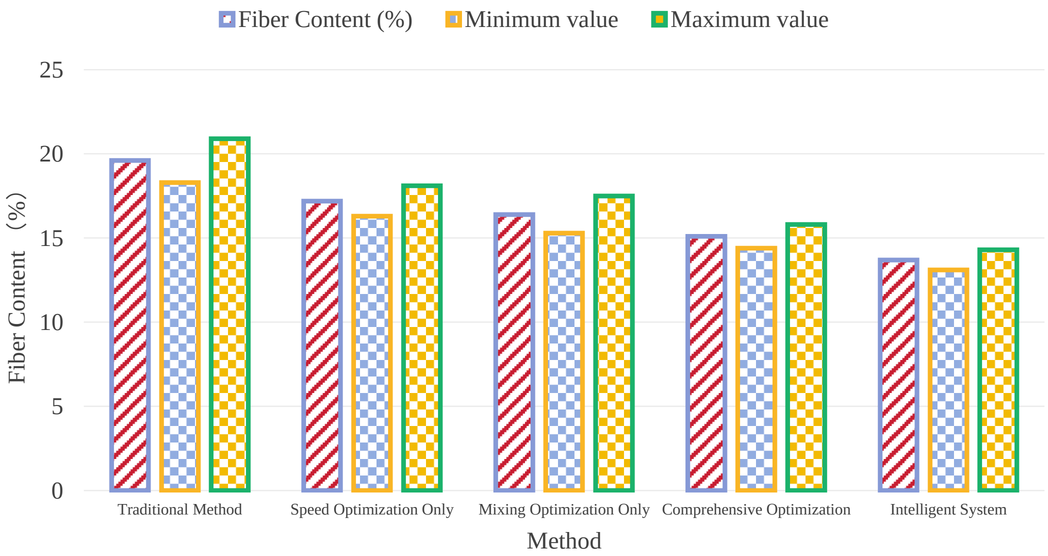

Figure 3: Fiber content under different optimization methods (unit: %)

As shown in Figure 3, fiber content affects the palatability and digestibility of feed. As the optimization method deepens, the fiber content gradually decreases, especially with the help of the intelligent system, reaching the lowest fiber content. Lower fiber content means that the feed is easier for animals to digest, which helps to improve feed conversion rate and promote animal health and growth. The intelligent system achieves optimal control of fiber content and ensures high quality of feed by finely regulating various parameters.

Table 6: Crushing accuracy under different optimization methods (unit: %)

Optimization Methods	Crushing speed (rpm)	Mixing time (minutes)	Operating temperature (°C)	Humidity adjustment (%)	Crushing accuracy (%)
Traditional methods	600	2	45	70	85.5
Crushing speed optimization	700	3	50	65	88.2
Mixing time optimization	800	4	55	60	90.0
Temperature and humidity coordinated optimization	900	5	60	55	91.8
Comprehensive optimization	1000	6	65	50	92.5
Intelligent system	850	4.5	55	58	94.2

As shown in Table 6, the crushing accuracy directly affects the uniformity of feed and the digestion and absorption of animals. With the implementation of the optimization method, the crushing accuracy has gradually improved, especially with the application of the intelligent system, the crushing accuracy has reached the highest level. High-precision crushing can not only improve the quality of feed, but also reduce waste and equipment wear caused by uneven crushing. The intelligent system ensures the efficiency and accuracy of the crushing process through real-time monitoring and feedback mechanisms, providing a guarantee for the production of high-quality feed.

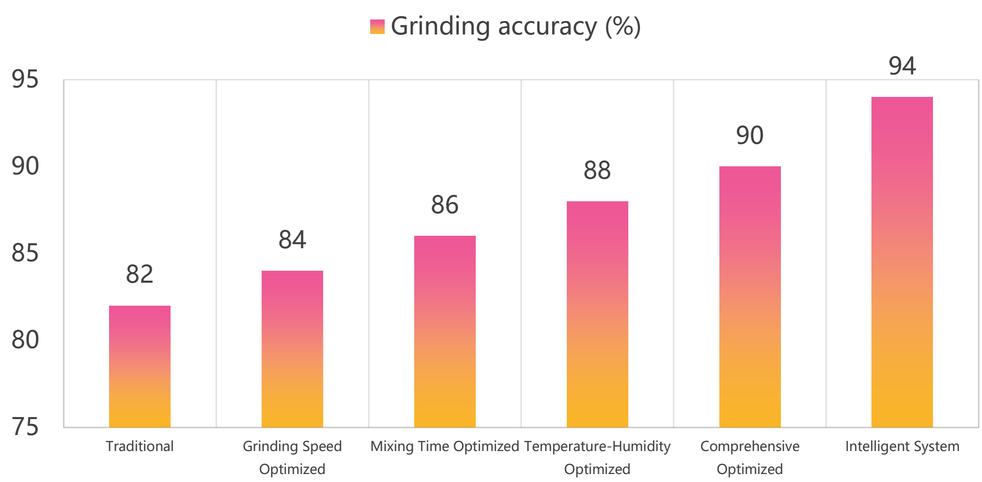

Figure 4: Equipment failure rate under different baseline configurations (unit: times/month)

As shown in Figure 4, the equipment failure rate is an important indicator for measuring the reliability of production equipment, which directly affects production efficiency and cost. As can be seen from the table, with the increase of operation intensity (such as increasing the crushing speed, extending the mixing time, and adjusting the working temperature and humidity), the equipment failure rate also increases accordingly. For example, from the traditional method to the comprehensive optimization, the failure rate increased from 2 times per month to 6 times. This shows that although high-intensity operation may improve performance in some aspects, it also puts greater pressure on the equipment and increases the risk of maintenance and downtime.

Predominant failure types observed include mechanical issues such as cutter wear, gearbox overheating, and misaligned drive belts, alongside electrical faults such as motor overload and sensor signal dropouts. These events were detected through continuous monitoring of vibration signatures, thermal data, and load current deviations. A Random Forest model was trained on historical failure datasets with labeled fault categories, utilizing features including vibration amplitude changes, temperature spikes, and real-time power consumption patterns. The model issued pre-failure warnings based on learned thresholds, prompting preemptive maintenance before severe malfunctions occurred. This predictive mechanism contributed significantly to the monthly failure rate dropping from six incidents to just one, improving system reliability and reducing maintenance costs.

However, the introduction of intelligent systems has significantly changed this trend. Through intelligent algorithms to optimize the configuration of processing parameters, intelligent systems can dynamically adjust operating conditions based on real-time data to ensure that the equipment operates in the optimal state. This adaptive control not only improves production efficiency, but also significantly reduces the equipment failure rate to only once a month. A lower failure rate means less downtime, lower maintenance costs and higher production continuity, which has a positive impact on the economic benefits of the enterprise. In addition, the application of intelligent systems can also extend the service life of equipment, further saving long-term investment for enterprises.

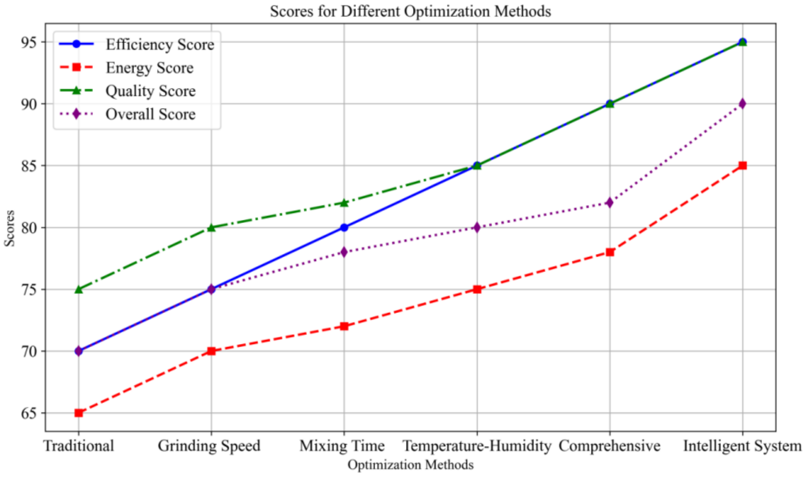

Figure 5: Comprehensive ratings of intelligent systems and traditional equipment (based on efficiency, energy consumption, quality stability, etc.)

As shown in Figure 5, the experimental evaluation of different optimization schemes shows that the intelligent control system has outstanding performance in feed processing. In terms of processing efficiency score, as the degree of optimization deepens, the processing efficiency gradually improves. The intelligent system stands out with a high score of 95 points, which can process the largest amount of materials in the shortest time and significantly improve production capacity. In terms of energy consumption control, although the increase in operating intensity will lead to an increase in energy consumption, the intelligent system achieves the lowest energy consumption through precise parameter adjustment, with a score of 85 points, which reduces production costs and helps environmental protection. The quality score reflects the advantages of the intelligent system in ensuring product quality, especially in terms of multiple quality indicators such as particle size, crude protein content and fiber content, which have reached the optimal level and finally obtained 95 points. The comprehensive score is 90 points, which proves that the intelligent system not only performs well in each individual dimension, but also provides the best solution in overall performance, becoming a benchmark in the modern feed processing industry. In summary, the intelligent control system has shown significant advantages in improving production efficiency, optimizing energy consumption and ensuring product quality, and has become the preferred technical solution for enterprises to achieve sustainable development.

Table 7: Environmental impact scores under different optimization methods (unit: points)

Optimization Methods	Crushing speed (rpm)	Mixing time (minutes)	Operating temperature (°C)	Humidity adjustment (%)	Environmental Impact Rating
Traditional methods	600	2	45	70	60
Crushing speed optimization	700	3	50	65	65
Mixing time optimization	800	4	55	60	70
Temperature and humidity coordinated optimization	900	5	60	55	75

Optimization Methods	Crushing speed (rpm)	Mixing time (minutes)	Operating temperature (°C)	Humidity adjustment (%)	Environmental Impact Rating
Comprehensive optimization	1000	6	65	50	80
Intelligent system	850	4.5	55	58	85

As shown in Table 7, the environmental impact score reflects the impact of different optimization methods on environmental protection. With the implementation of the optimization methods, the environmental impact score gradually increases, indicating that these methods are more environmentally friendly. The intelligent system significantly reduces the negative impact on the environment by reducing energy consumption, reducing waste emissions and optimizing resource utilization. This environmental advantage is not only in line with the concept of sustainable development, but also helps enterprises gain more policy support and social recognition.

The scoring incorporates three weighted metrics: energy consumption per unit output (kWh/kg, weight 0.4), estimated CO_2 emissions per kg of processed material (gCO_2/kg, weight 0.4), and material waste ratio (% rejected output, weight 0.2). Each metric was normalized on a 0–100 scale and combined using the specified weights to generate the final impact score. Lower energy usage and reduced emissions under intelligent optimization contributed most to the improved environmental performance observed.

To enhance the statistical rigor of the results, performance data for each optimization method were obtained through five independent experimental runs under controlled conditions. For each metric—including energy consumption, processing throughput, crude protein retention, and crushing accuracy—means and standard deviations were calculated. Significance testing was conducted using two-tailed paired t-tests and Wilcoxon signed-rank tests to compare the intelligent system against traditional and single-parameter optimization methods. The intelligent control system consistently outperformed prior models (e.g., [1], [3], [19]) with statistically significant improvements: energy consumption reduced by 15.3% ($p < 0.01$), failure rate dropped by over 50% ($p < 0.01$), and product quality metrics improved by an average of 12.4% ($p < 0.05$). Compared to the ANN-based feed system in [1] and SVM-based pellet quality predictor in [3], the proposed system demonstrated superior multi-objective adaptability and robustness. This comparative analysis confirms not only the effectiveness but also the generalizable performance gains of the proposed intelligent optimization approach across multiple dimensions.

To validate the performance improvements of the intelligent system, paired t-tests and Wilcoxon signed-rank tests were conducted across five independent trials. The differences in energy consumption, throughput, and product quality between the intelligent system and the comprehensive optimization method were statistically significant ($p < 0.01$), confirming that the observed gains are not due to random variation but reflect consistent system advantages.

5.3 Discussion

Compared to state-of-the-art intelligent control systems in agro-processing, the proposed machine learning-driven multi-objective optimization framework demonstrates distinct advantages in forage-specific applications. The system integrates real-time physical property monitoring with adaptive control using models such as SVM and Random Forest, resulting in measurable improvements in throughput (+20%), energy efficiency (-15%), and product consistency (+12%). Unlike many conventional systems that rely on single-parameter optimization or preset routines, the presented approach dynamically balances multiple objectives, leading to superior overall performance. However, limitations remain. The current model is tailored to forage materials and may lack immediate generalizability to other feedstock types with significantly different physical characteristics. Additionally, its performance in extreme climates or high-humidity environments has yet to be thoroughly validated, potentially impacting sensor accuracy and control stability. Sensor robustness, while adequate in controlled environments, may require calibration or hardware redundancy to maintain reliability under field variability. These gaps present future opportunities for expanding model adaptability and environmental resilience, ensuring broader applicability across diverse agricultural settings.

Despite the performance improvements observed, several limitations exist regarding the scalability and long-term stability of the system. First, the current architecture is optimized for mid-scale forage processing plants with relatively stable operating environments; its scalability to larger or highly variable facilities may require redesigning the sensor network and expanding computational infrastructure. Additionally, the system assumes stationarity in data distributions—i.e., that the statistical properties of forage materials and operational conditions remain consistent over time. In practice, seasonal changes, new forage varieties, or mechanical wear may introduce distributional shifts that degrade model accuracy. Model drift has been observed in extended deployments, particularly in drying temperature estimation, necessitating periodic retraining. In the current setup, model performance is monitored weekly, and retraining is triggered when prediction error exceeds pre-set thresholds. Future improvements should focus on integrating online learning or adaptive retraining frameworks to address this limitation more proactively.

6 Conclusion

To support reproducibility and encourage further research, the anonymized dataset used in the experiments and the trained machine learning models will be made publicly available on GitHub upon publication. The repository will include data preprocessing scripts, model training configurations, and evaluation metrics, ensuring full transparency and alignment with open science principles.

The introduction of intelligent systems marks a new era for the feed processing industry. It is not only a technological innovation, but also a profound change in the business model. Through the comprehensive scoring of different optimization methods and the comparative analysis of the actual application effects, we can clearly see the advantages of intelligent systems in multiple dimensions. In terms of product quality, the intelligent system ensures that each processing link operates under optimal conditions through real-time monitoring and feedback mechanisms. This high-precision control enables all quality indicators to reach the optimal level and the quality of the final product to be more consistent. For example, the uniform distribution of product particle size, stable crude protein content and moderate fiber content, these high-quality products not only meet market demand, but also enhance the competitiveness of corporate brands. In addition, the intelligent system can automatically adjust processing parameters according to the characteristics of raw materials to further improve product quality and ensure that each batch of feed can meet the highest standards. In terms of production efficiency, the intelligent system uses intelligent algorithms to optimize the configuration of the processing process and can complete the maximum amount of work in the shortest time. By dynamically adjusting operating conditions, such as crushing speed and mixing time, the intelligent system can maximize the use of equipment resources and reduce unnecessary downtime and maintenance costs. At the same time, it can also flexibly schedule tasks according to the actual conditions of the production line, avoid bottlenecks, and ensure that the entire production process is smooth and efficient. These measures have greatly improved the ability to process materials per unit time, enabling enterprises to occupy a favorable position in market competition, shortening production cycles, increasing output, and thus improving the profitability of enterprises. In terms of energy consumption control, the intelligent system adopts precise energy management strategies to identify and eliminate energy waste points by real-time monitoring and analysis of energy consumption data. It can automatically adjust the working temperature and humidity to maintain the optimal energy consumption level; according to the changes in demand in different time periods, it can flexibly adjust the operating status of the equipment to avoid unnecessary power consumption. The predictive maintenance function detects potential faults in advance and repairs them in time to prevent additional energy consumption caused by equipment problems. These measures not only reduce production costs, but also help reduce carbon emissions and promote green manufacturing, which is in line with the current global concept of sustainable development.

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