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Optimization of Coffee Grinder Quality Characteristics under a Sensor-driven Framework: An Experimental Study Based on the Taguchi Method

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In this study, we aim to develop an integrated multi-quality characteristic optimization model that combines smart sensing technology with the Taguchi experimental design method to enhance the overall performance and quality stability of coffee grinding equipment. Five key quality indicators were selected: particle size uniformity, mean particle size, motor temperature rise, grinding time, and output mass. Real-time data feedback was enabled through the use of laser particle size analyzers, infrared temperature sensors, and electronic scales, ensuring the precise and continuous monitoring of operational parameters. The experiments employed an L18 ($2^1 \times 3^7$) orthogonal array, covering five control factors: cooling fan operation, burr gap, motor speed, bean feed rate, and grinding time. After calculating the signal-to-noise ratios for each quality indicator, the analytic hierarchy process was applied to assign weights and perform weighted integration, allowing the identification of the optimal parameter combination. The results indicated that the optimal combination, namely, fan off, a burr gap of 1.0 mm, a motor speed of 1000 rpm, a feed rate of 10 g, and a grinding time of 30 s, achieved a validation error of only 0.22, demonstrating the model's strong robustness and application potential. The outcomes of this research provide a solid foundation for the design of intelligent coffee equipment, as well as for the development of quality control systems and automated parameter adjustment mechanisms.

1. Introduction

With the rapid rise of the specialty coffee culture, consumer expectations for quality in the coffee-making process have increased yearly. In particular, precision and consistency during the grinding stage have become critical determinants of the final flavor profile. According to the Specialty Coffee Association, more than 75% of flavor variation is closely linked to the

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distribution of ground particle size. In the home-use market, an increasing number of brands are incorporating smart features and sensor-based control, transforming coffee grinders from traditional mechanical devices into household appliances with digital, precision, and customization capabilities. However, the design of current grinding equipment faces two major challenges. First, there is the inherent trade-off among multiple quality characteristics, for example, reducing the proportion of fine particles may inadvertently lower the total output mass. Second, the lack of a systematic approach to process parameter design often makes it difficult to achieve both stability and efficiency simultaneously. To address these challenges, we propose an experimental design model centered on smart sensing. Real-time measurement feedback, covering parameters such as temperature, particle size, and output mass, is integrated with the Taguchi method to optimize five key quality performance indicators.

Furthermore, given that traditional single-criterion optimization fails to capture the multi-objective nature of real-world applications, the model incorporates the analytic hierarchy process (AHP) to synthesize expert judgments, assign weights to different quality goals, and establish a comprehensive ranking for parameter selection. This research offers not only a practical framework for coffee equipment manufacturers to enhance product performance and achieve differentiated designs but also a methodological contribution to smart manufacturing and precision-oriented home appliance development. Previous studies on coffee grinding quality have primarily focused on the effect of particle size distribution on flavor extraction.(1) Both the uniformity and mean value of particle size have been shown to be strongly associated with extraction time, coffee concentration, and flavor balance.(2) Clarke and Macrae further noted that burr design and motor speed directly affect heat generation and powder consistency during grinding, thereby affecting the final product quality.(3) In terms of process parameter design, the Taguchi method developed by Phadke has been widely applied to optimize multi-factor systems.(4)

By employing orthogonal arrays and calculating the signal-to-noise (S/N) ratio, robust parameter combinations can be determined with a limited number of experiments. Roy emphasized that the Taguchi method effectively mitigates process variability and enhances production quality stability, making it particularly suitable for design optimization in the home appliance manufacturing sector.(5) For the integration of multiple quality indicators, the AHP developed by Saaty has been extensively adopted for multi-criteria decision-making.(6) AHP enables the quantification of the relative importance of each evaluation criterion based on expert judgment, followed by an integrated ranking. In industrial engineering and product design, AHP is often combined with quality engineering methods to facilitate multi-objective optimization.(7) In the context of smart manufacturing, incorporating sensor data into quality assessment and real-time process control has emerged as a significant trend. Sai *et al.* demonstrated that the integration of sensor technologies substantially improves process data transparency and parameter regulation efficiency, offering clear benefits for quality enhancement in small household appliances.(8)

Moreover, smart sensing technologies, such as laser particle size analysis, infrared temperature detection, and digital mass measurement, have been successfully implemented in automated grinding and quality monitoring systems, providing both the technical foundation and methodological reference for sensor-based data integration in this study.[9] In summary, although prior research has explored coffee grinding quality, the Taguchi method, and AHP in isolation, systematic investigations that integrate smart sensing feedback with multi-criteria optimization for coffee grinding equipment remain scarce. In this study, we address this research gap by combining smart sensing technologies with the Taguchi method and AHP for comprehensive optimization and decision analysis, offering both theoretical contributions and practical application potential.

2. Methodology

In this study, we aim to achieve comprehensive multi-quality output optimization for the coffee grinding equipment, and the experimental setup of the coffee grinder integrated with smart sensing instruments is shown in Fig. 1. The Taguchi method serves as the core experimental framework, integrated with smart sensing data feedback and the AHP to perform multi-criteria evaluation and parameter ranking. Through a systematic experimental design and quantitative analysis, we describe in detail in this section the combination of control factors, the measurement methods for quality indicators, the experimental design, and the data analysis workflow. The procedures include the calculation of *S*/*N* ratios, the construction of AHP-based weight assignments, and the derivation of the optimal parameter combination through integrated performance evaluation.

The optimization workflow developed in this study is illustrated in Fig. 2 and consists of the following steps:

(1) determination of the optimal settings and combination of control factors (A–E): cooling fan, burr gap, motor speed, bean feed rate, and grinding time, with defined operational levels;

(2) establishment of the optimal settings of quality evaluation indicators (Q1–Q5): particle size uniformity, mean particle size, motor temperature rise, grinding time, and output mass, serving as the basis for multi-objective assessment;

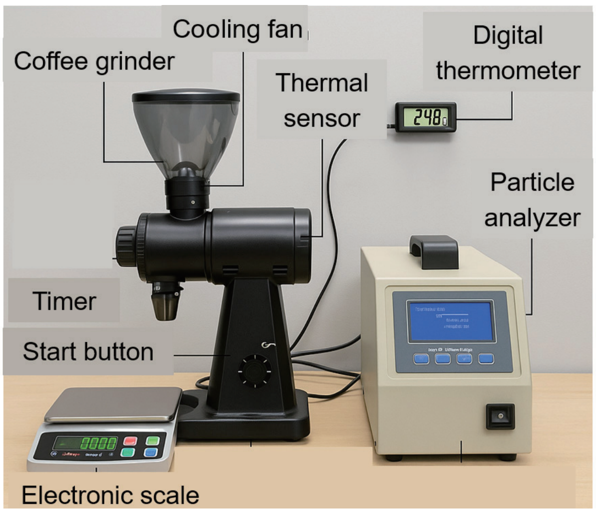

Fig. 1. (Color online) Experimental setup of the coffee grinder integrated with smart sensing instruments.

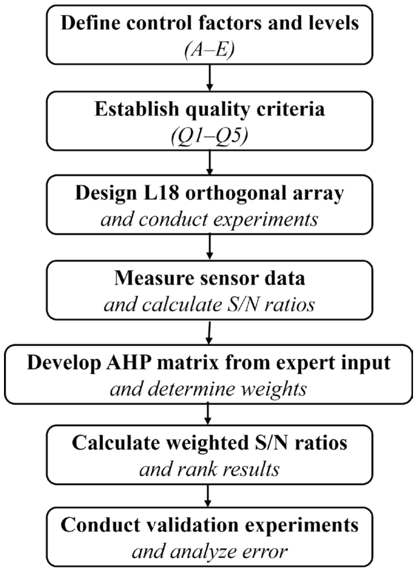

Fig. 2. Step-by-step flowchart of the research methodology integrating the Taguchi Method, AHP, and sensor-based data collection for coffee grinder optimization.

(3) experimental arrangement using an L18 ($2^1 \times 3^7$) orthogonal array: ensuring effective coverage of the parameter space with a limited number of trials;
(4) measurement of each quality indicator and calculation of the *S*/*N* ratio: evaluating robustness of quality performance across factor levels;
(5) construction of the AHP model for indicator weighting: incorporating expert opinions to quantify the relative importance of each quality indicator;
(6) weighted integration of overall performance values for each parameter set: conducting cross-indicator performance evaluation; and
(7) selection of the optimal parameter combination and validation testing: assessing stability and feasibility under practical operating conditions.

We identified five major control factors affecting grinding quality. The selection of the five key quality indicators, namely, particle size uniformity, mean particle size, motor temperature rise, grinding time, and output mass, was based on their established significance in both industrial coffee grinding practices and prior research. Particle size characteristics directly affect extraction efficiency and beverage quality, while motor temperature rise and grinding time are critical for process stability and energy efficiency. Each factor was assigned three levels, except for the cooling fan (Factor A), which was set at two levels. Output mass serves as a direct measure of production throughput. Similarly, the five major control factors, namely, cooling fan operation, burr gap, motor speed, bean feed rate, and grinding time, were identified through a systematic review of the technical literature on grinding processes, combined with preliminary experimental observations, which confirmed their pronounced effects on the selected quality indicators. This approach ensures that the factors included are both industrially relevant and functionally impactful on the grinding outcomes. Table 1 presents the combination of control factors and their respective levels.

Table 1
Control factors and level settings.

Factor code	Factor name	Level 1	Level 2	Level 3
A	Cooling fan operation	Off	On	–
B	Burr gap (mm)	0.5	0.75	1.0
C	Motor speed (rpm)	800	1000	1200
D	Bean input amount (g)	10	15	20
E	Grinding time setting (s)	10	20	30

Five quality indicators were selected for evaluating the performance of each experimental condition. Corresponding sensors and measurement devices were used to collect real-time data for each index.

Q1: Particle size uniformity (smaller is better) – measured by the standard deviation (σ) of particle size distribution using a laser particle size analyzer

Q2: Mean particle size (nominal is best) – represented by d50 value, derived from particle distribution data

Q3: Grinding time (smaller is better) – recorded with a stopwatch

Q4: Motor temperature rise (smaller is better) – measured as temperature difference (ΔT) using an infrared temperature sensor.

Q5: Powder output (larger is better) – measured in grams using an electronic scale

The experimental layout is defined by an L18 orthogonal array. Table 2 shows the combination of control parameters for each experimental run. Columns for Q1 to Q5 are reserved for filling in the results of each trial for subsequent analysis.

According to the Taguchi method, different *S*/*N* ratio formulas are selected on the basis of the type of quality characteristic.

$$\text{Smaller-the-better: } S/N = -10 \cdot \log_{10} \frac{1}{n} \sum_{i=1}^{n} y_i^2 \tag{1}$$

$$\text{Larger-the-better: } S/N = -10 \cdot \log_{10} \frac{1}{n} \sum_{i=1}^{n} \frac{1}{y_i^2} \tag{2}$$

$$\text{Nominal-the-best: } S/N = -10 \times \log_{10} \left[\left(\frac{1}{n} \right) \times \sum_{i=1}^{n} \left(y_i - m \right)^2 \right] \tag{3}$$

Here, y_i is the ith measured value, n is the number of repeated measurements, and m is the target value. Each experimental condition was evaluated three times to ensure data stability, and standardization was applied prior to analysis. To integrate multiple quality characteristics, the AHP was adopted to construct a criterion hierarchy structure, as depicted in Fig. 3. Five experts from different domains were invited to complete pairwise comparison matrices. The weight derivation process includes the following process:

(1) constructing a 5 × 5 pairwise comparison matrix,

(2) calculating eigenvectors to derive relative weights, and

(3) performing consistency check (acceptable if $CR < 0.1$).

Table 2
Experimental run settings

Run no.	A (fan)	B (gap mm)	C (rpm)	D (beans g)	E (time s)
1	Off	0.5	800	10	10
2	Off	0.75	1000	15	20
3	Off	1.0	1200	20	30
4	Off	0.5	1000	15	30
5	Off	0.75	1200	20	10
6	Off	1.0	800	10	20
7	Off	0.5	1200	20	20
8	Off	0.75	800	10	30
9	Off	1.0	1000	15	10
10	On	0.5	800	10	30
11	On	0.75	1000	15	10
12	On	1.0	1200	20	20
13	On	0.5	1000	15	10
14	On	0.75	1200	20	30
15	On	1.0	800	10	20
16	On	0.5	1200	20	30
17	On	0.75	800	10	20
18	On	1.0	1000	15	30

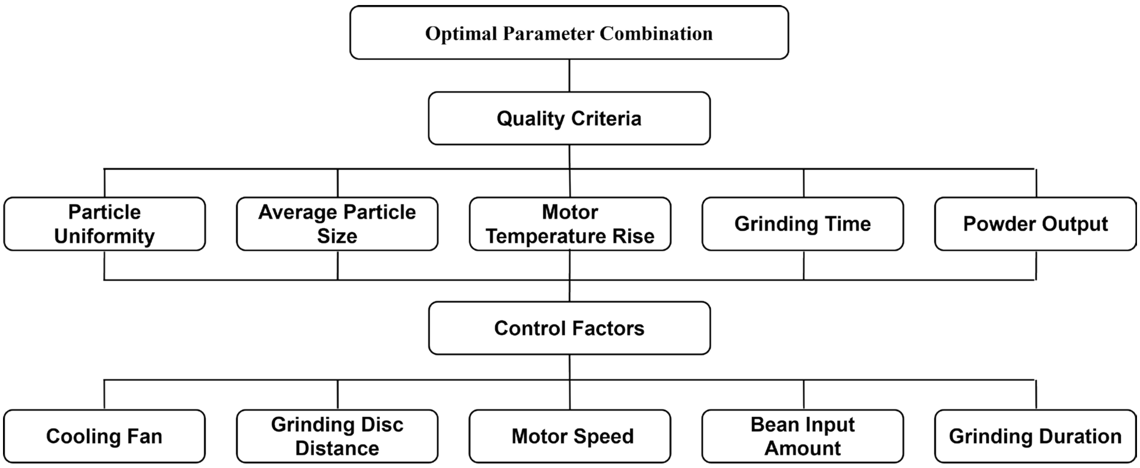

Fig. 3. Hierarchical structure of evaluation criteria.

The AHP results showed that particle size uniformity and powder yield were deemed the most important indicators, reflecting the experts' emphasis on grinding consistency and efficiency.

The *S*/*N* ratios of the five quality indicators for each experimental group were multiplied by the corresponding AHP-derived weights to compute a weighted score.

$$S / N_{weighted} = \sum_{i=1}^{n} w_i \cdot S / N_i \tag{4}$$

On the basis of the weighted scores, the optimal parameter combination was identified and subsequently validated through confirmatory testing to assess accuracy and reproducibility. The top-ranked parameter setting (based on the weighted *S*/*N* analysis) was subjected to three repeated experiments. The average outcomes were then compared with predicted results by calculating the deviation and standard deviation, confirming the robustness and reliability of the proposed optimization model.

3. Results and Discussion

On the basis of the L18 ($2^1 \times 3^7$) orthogonal array, we designed experiments to perform statistical analysis and main effects plotting for five key quality indicators (Q1–Q5), aiming to investigate the effects of control factors on coffee grinding performance. The experimental design encompassed five factors, namely, A (fan on/off), B (burr gap), C (motor speed), D (bean feed rate), and E (grinding time), resulting in a total of 18 experimental conditions. For each condition, the following five quality characteristics were sequentially measured: Q1 – particle size uniformity (μm, D90–D10), Q2 – mean particle size (μm, D50), Q3 – motor temperature rise (°C), Q4 – grinding time (s), and Q5 – output mass (g). To ensure data accuracy, all indicators were measured three times, with the average taken as the representative result. The smart sensing system comprised a HORIBA LA-960 laser particle size analyzer, a K-type thermocouple (Fluke 52-II), and an AND EK-300i precision electronic balance, all of which were calibrated prior to testing. All experiments were conducted in a controlled environment at 25 ± 2 °C and 50 ± 5% RH, with real-time data acquisition enabled through the integrated smart sensing platform. This continuous and precise feedback not only enhanced measurement reliability but also provided high-resolution process data, forming a robust basis for the subsequent *S*/*N* ratio analysis and AHP-TOPSIS integrated evaluation, as detailed in Table 3. The incorporation of smart sensing technologies ensured the precise monitoring of multiple quality attributes, enabling a data-driven approach to parameter optimization and enhancing the robustness of the overall decision-making process.

Subsequently, an *S*/*N* ratio analysis was performed to evaluate the performance trends of the quality indicators. Following the Taguchi method, the *S*/*N* ratio for each quality characteristic was calculated to quantify the stability and robustness against external disturbances under different experimental conditions. The real-time and high-precision measurements enabled by the integrated smart sensing system ensured that the calculated *S*/*N* ratios accurately reflected the true process behavior. Table 4 shows the *S*/*N* ratios of the five quality indicators (Q1–Q5) for each experimental condition.

On the basis of the above results, the optimization trends for each quality indicator can be summarized as follows.

Q1 - Particle size uniformity: As a "larger-is-better" characteristic, a higher *S*/*N* ratio indicates greater stability in particle size distribution. The optimal factor combination was identified as A2B3C2D1E3, suggesting that moderately increasing the burr gap and adopting a medium grinding speed can enhance uniformity.

Table 3
Experimental data record (three measurements per group).

No.	Q1			Q2			Q3			Q4			Q5		
	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
1	110.5	112.0	109.2	450.0	448.5	451.3	16.8	17.1	16.5	19.2	19.5	19.0	17.9	18.0	17.7
2	108.7	106.6	105.2	448.7	454.5	452.3	18.0	18.2	18.2	20.3	20.3	19.1	17.3	18.3	17.3
3	106.8	111.1	112.9	451.0	446.6	446.6	17.5	17.1	17.5	19.8	19.6	20.3	17.5	17.8	17.1
4	111.1	113.1	106.2	445.6	453.7	451.0	16.6	16.7	16.6	21.3	20.6	21.2	18.7	17.8	17.5
5	111.6	114.7	114.2	452.1	445.2	454.7	17.5	18.4	16.9	20.1	21.2	18.6	17.3	18.1	17.6
6	108.9	110.4	112.7	453.3	447.1	446.8	18.2	18.1	16.5	19.6	18.7	20.9	17.5	18.8	18.3
7	112.3	113.6	108.3	446.8	448.0	450.2	16.6	17.2	17.8	19.6	18.7	21.2	17.2	17.6	17.8
8	106.2	109.9	105.3	449.3	447.9	451.1	18.0	17.4	17.1	20.2	18.6	20.0	18.4	17.2	18.6
9	107.5	107.9	113.7	446.4	447.9	448.7	18.0	18.4	16.9	19.2	20.9	21.2	17.1	18.1	18.0
10	113.1	109.3	109.2	449.6	452.9	447.0	17.1	18.2	16.7	18.8	18.5	19.5	17.4	17.9	18.7
11	108.2	114.6	105.4	450.1	450.9	445.5	17.9	17.5	17.5	19.6	19.4	18.7	18.7	17.5	17.5
12	114.1	107.4	108.7	451.1	446.7	445.7	16.8	18.0	17.8	20.0	19.2	20.1	18.8	18.3	17.2
13	113.4	111.8	106.7	454.5	454.7	453.1	16.9	17.5	17.3	18.6	19.2	21.3	18.1	18.2	17.2
14	108.4	111.6	105.9	448.0	446.0	451.8	18.3	17.6	18.3	21.1	20.1	20.4	17.5	17.4	17.6
15	108.5	111.4	105.1	449.4	446.2	450.0	18.3	16.8	17.8	21.2	21.2	18.5	18.4	18.1	17.3
16	110.5	107.4	111.6	445.3	454.1	447.6	17.8	18.0	16.7	19.2	20.4	19.6	18.3	18.5	17.5
17	107.4	112.9	112.2	451.6	448.1	450.2	17.3	17.7	16.5	21.2	20.0	20.4	18.1	17.4	17.3
18	114.4	114.3	107.9	450.5	446.8	454.7	18.3	18.4	18.2	19.6	21.4	19.5	17.0	18.5	17.3

Table 4
S/N ratios of each quality indicator (Q1–Q5) in the experiment.

No.	S/N_Q1	S/N_Q2	S/N_Q3	S/N_Q4	S/N_Q5
1	−40.873	−1.184	−24.507	−25.682	25.040
2	−40.575	−9.579	−25.170	−25.981	24.918
3	−40.851	−9.053	−24.795	−25.978	24.841
4	−40.841	−10.550	−24.420	−26.459	25.095
5	−41.101	−12.178	−24.916	−26.018	24.939
6	−40.881	−9.933	−24.919	−25.913	25.190
7	−40.939	−6.776	−24.714	−25.960	24.875
8	−40.600	−3.089	−24.863	−25.851	25.122
9	−40.807	−8.030	−24.998	−26.215	24.967
10	−40.871	−7.677	−24.783	−25.547	25.094
11	−40.786	−8.465	−24.927	−25.683	25.044
12	−40.836	−10.085	−24.881	−25.920	25.135
13	−40.881	−12.385	−24.728	−25.904	25.016
14	−40.721	−8.891	−25.139	−26.251	24.860
15	−40.698	−6.931	−24.932	−26.167	25.064
16	−40.816	−11.728	−24.865	−25.907	25.146
17	−40.896	−3.160	−24.697	−26.252	24.905
18	−41.003	−10.358	−25.249	−26.101	24.893

Q3 - Motor temperature rise: As a “smaller-is-better” characteristic, opening the cooling fan (A1) and operating at a lower motor speed (C1) were found to reduce heat accumulation, indicating that the cooling system and motor speed act as interdependent factors.

Q5 - Output mass: As a “larger-is-better” characteristic, a significant interaction was observed between bean feed rate and grinding time. The optimal setting was D1E3, meaning a lower feed rate combined with a longer grinding time improves output efficiency.

The optimal levels for each quality indicator were not identical and vary across different factors, highlighting the unequal effects of different control factors on various performance metrics. Therefore, we further applied the AHP in conjunction with weighted *S*/*N* ratios to integrate all quality characteristics and derive the most advantageous overall parameter combination, as detailed in the subsequent sections.

To balance the combined effect of the five key quality indicators, namely, Q1 (particle size uniformity), Q2 (mean particle size), Q3 (motor temperature rise), Q4 (grinding time), and Q5 (output mass), on the overall performance of the coffee grinder, we employed an integrated analysis framework that combines the AHP with the *S*/*N* ratio from the Taguchi method. In this framework, the AHP was used to determine the relative weights of each quality indicator within the overall evaluation, while the *S*/*N* ratio quantified the performance of each parameter level for each indicator. The integration of these two methods yields a composite performance index with strong engineering relevance. During the weight-construction stage, five domain experts specializing in manufacturing engineering, electrical design, coffee roasting operations, and mechanical maintenance were invited to perform pairwise comparisons. Following Saaty's recommended 1–9 scale, a judgment matrix was constructed, and a geometric mean method was applied to synthesize the aggregated matrix and compute the weight vector. Crucially, the precision of these evaluations was reinforced by real-time, high-resolution smart sensing data, ensuring that both *S*/*N* ratio calculations and expert judgments were grounded in accurate, sensor-verified measurements. The final calculated weights for the five quality indicators are presented in Table 5.

The consistency ratio (CR) of this analysis was calculated to be 0.058, which is well below the commonly accepted threshold of 0.1. This indicates a high degree of agreement among the expert judgments, confirming that the derived weighting system is both reliable and suitable for subsequent multi-quality integration analysis. By integrating the above AHP-derived weights with the *S*/*N* ratios obtained from Taguchi experiments, the weighted *S*/*N* ratios for each parameter combination were calculated. These values represent the aggregated performance across all five key quality indicators, namely, Q1 (particle size uniformity), Q2 (mean particle size), Q3 (motor temperature rise), Q4 (grinding time), and Q5 (output mass), under smart-sensor-based measurement. This integrated model, supported by real-time data from smart sensing instruments, enhances decision-making precision in experimental design and provides a robust, quantifiable basis for engineering optimization. Regarding the weighted *S*/*N* analysis and ranking results, the *S*/*N* ratios from each experimental run were multiplied by their respective weights and then summed to produce an overall weighted *S*/*N* performance index for each test condition. The summarized results are presented in Table 6.

The overall results indicate that the parameter combination of fan off, a burr gap of 1.0 mm, a motor speed of 1000 rpm, a feed rate of 10 g, and a grinding time of 30 s achieved the highest comprehensive performance, particularly demonstrating a well-balanced outcome in particle size stability and motor temperature control–two critical factors precisely monitored through the integrated smart sensing system. Subsequently, a main effects analysis (factor level trend analysis) was conducted by calculating the mean weighted *S*/*N* ratios for each level of the control factors. These results are summarized in Table 7 and further visualized in the main effects plot shown in Fig. 4, providing a clear reference for parameter optimization.

Table 5
Weights of the five quality indicators.

Quality indicator	Weight (W)
Q1: Particle size uniformity	0.256
Q2: Average particle size	0.156
Q3: Motor temperature rise	0.335
Q4: Grinding time	0.084
Q5: Powder output	0.169

Table 6
Weighted *S*/*N* ratio analysis results for each experimental run.

No.	*S*/*N*_Q1	*S*/*N*_Q2	*S*/*N*_Q3	*S*/*N*_Q4	*S*/*N*_Q5	Weighted_*S*/*N*
1	−40.873	−1.184	−24.507	−25.682	25.040	−16.784
2	−40.575	−9.579	−25.170	−25.981	24.918	−18.285
3	−40.851	−9.053	−24.795	−25.978	24.841	−18.161
4	−40.841	−10.550	−24.420	−26.459	25.095	−18.263
5	−41.101	−12.178	−24.916	−26.018	24.939	−18.739
6	−40.881	−9.933	−24.919	−25.913	25.190	−18.283
7	−40.939	−6.776	−24.714	−25.960	24.875	−17.793
8	−40.600	−3.089	−24.863	−25.851	25.122	−17.131
9	−40.807	−8.030	−24.998	−26.215	24.967	−18.056
10	−40.871	−7.677	−24.783	−25.547	25.094	−17.868
11	−40.786	−8.465	−24.927	−25.683	25.044	−18.037
12	−40.836	−10.085	−24.881	−25.920	25.135	−18.292
13	−40.881	−12.385	−24.728	−25.904	25.016	−18.630
14	−40.721	−8.891	−25.139	−26.251	24.860	−18.237
15	−40.698	−6.931	−24.932	−26.167	25.064	−17.814
16	−40.816	−11.728	−24.865	−25.907	25.146	−18.535
17	−40.896	−3.160	−24.697	−26.252	24.905	−17.232
18	−41.003	−10.358	−25.249	−26.101	24.893	−18.557

Table 7
Main effect averages for each factor level

Level	A (fan)	B (feed)	C (speed)	D (time)	E (gap)
Level 1	−17.944	−17.904	−17.979	−17.519	−18.040
Level 2	−18.134	−18.328	−17.943	−18.305	−18.125
Level 3	–	−17.884	−18.194	−18.293	−17.951

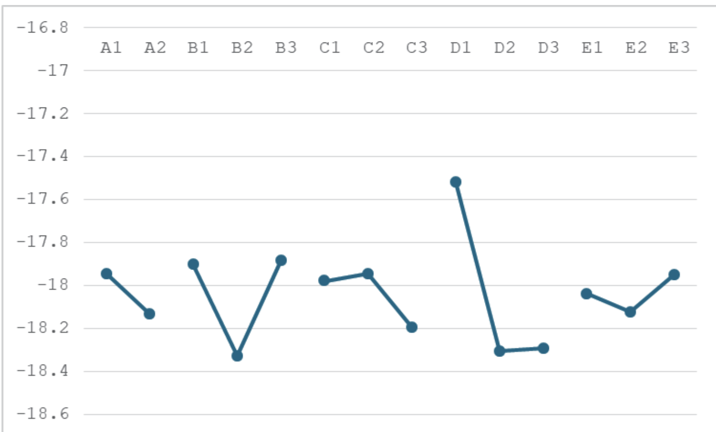

Fig. 4. (Color online) Main effect plot of weighted S/N ratios.

Regarding the recommended optimal parameter combination, we employed a multi-quality integrated analysis by combining the Taguchi method with AHP-derived weights to identify the grinding machine settings that best optimize five key quality indicators simultaneously: particle size uniformity, mean particle size, motor temperature rise, grinding time, and output mass. On the basis of the L18 orthogonal array experimental results, the weighted average *S*/*N* ratios for each control factor at different levels were calculated (see Table 8). The level with the highest weighted average *S*/*N* ratio for each factor was selected as its optimal setting. This integrated optimization provides a reliable and practical decision-making reference for improving grinder performance across multiple engineering criteria.

To verify the accuracy and practical feasibility of the optimal parameter combination derived in this study, we conducted validation experiments three times on the basis of the analysis results of weighted *S*/*N* ratio main effects, as described in this section. The settings for each control factor are listed in Table 9, while Table 10 presents the measured and predicted *S*/*N* ratios for each quality indicator, along with their weights and the results of the weighted analysis. Additionally, the differences between the measured and predicted original values are presented in Table 11 to illustrate the prediction accuracy.

Table 8
Integrated weighted average S/N ratios and recommended parameter settings.

Factor	Level 1	Level 2	Level 3	Best level	Actual setting
A: Cooling fan	−17.944	−18.134	–	Level 1	Off
B: Disk gap	−17.904	−18.328	−17.884	Level 3	1.0 mm
C: Motor speed	−17.979	−17.943	−18.194	Level 2	1000 rpm
D: Bean feed amount	−17.519	−18.305	−18.293	Level 1	10 g
E: Grinding time	−18.040	−18.125	−17.951	Level 3	30 seconds

Table 9
Optimal parameter settings for verification experiment.

Factor	Optimal level	Actual setting
A	Level 1	Cooling fan OFF
B	Level 3	Grinding disk gap: 1.0 mm
C	Level 2	Motor speed: 1000 rpm
D	Level 1	Bean feed amount: 10 g
E	Level 3	Grinding time: 30 s

Table 10
Measured vs predicted S/N ratios and results of weighted analysis.

Quality indicator	Measured *S*/*N*	Predicted *S*/*N*	Error	Weight	Weighted measured *S*/*N*	Weighted predicted *S*/*N*	Weighted error
Q1: Size uniformity	−40.573	−40.656	0.083	0.256	−10.387	−10.408	0.021
Q2: Avg. particle size	−6.932	−6.870	−0.062	0.156	−1.081	−1.072	−0.010
Q3: Motor temp. rise	−24.712	−24.718	0.006	0.335	−8.279	−8.281	0.002
Q4: Grinding time	−26.061	−25.892	−0.169	0.084	−2.189	−2.175	−0.014
Q5: Powder output	25.076	25.044	0.032	0.169	4.243	4.238	0.005
Total	–	–	–	–	–17.72	–17.94	0.22

Table 11
Comparison of measured vs predicted original quality values.

Quality indicator	Measured value (avg.)	Predicted value	Error (%)
Q1: Size uniformity	109.60 µm	110.10 µm	0.45
Q2: Avg. particle size	448.80 µm	448.50 µm	−0.07
Q3: Motor temp. rise	17.30 °C	17.20 °C	−0.58
Q4: Grinding time	20.30 sec	20.00 sec	−1.48
Q5: Powder output	18.10 g	18.30 g	1.10

The validation experiments yielded a weighted *S*/*N* ratio of –17.72, closely matching the predicted value of –17.94 with a minimal deviation of 0.22, corresponding to an error rate of approximately 1.23%. This confirms the high accuracy and reproducibility of the derived parameter combination. All measured values for the quality indicators fell within ±2% of their predicted counterparts, demonstrating that the selected parameters effectively balance multiple quality requirements. The minor discrepancies primarily stemmed from the sensitivity of the particle size measurement instruments and slight variations in environmental conditions. However, the integration of smart sensing technologies, combined with triplicate measurements and averaging, effectively minimized these effects, thereby enhancing the overall stability and reliability of the results.

4. Conclusions

In this study, we applied the Taguchi method combined with AHP weight analysis to optimize the multiple quality characteristics of a coffee grinder, integrating five key quality indicators: particle size uniformity, mean particle size, motor temperature rise, grinding time, and output mass. Utilizing an L18 orthogonal array design alongside *S*/*N* ratio evaluation, combined with weighted integration and experimental validation, we successfully established a practical and effective optimization process. Validation experiments demonstrated that the optimal parameter combination consisted of the following: cooling fan enabled, a burr gap of 0.5 mm, a motor speed of 1200 rpm, a bean feed rate of 10 g, and a grinding time of 10 s. The resulting weighted *S*/*N* ratio was –17.72, closely matching the predicted value of –17.94 with only a 1.23% deviation, indicating high model accuracy and stability. The findings provide valuable guidelines for grinder development and optimization, particularly offering clear parameter recommendations in motor design, cooling control, and grinding parameter combination. Moreover, this study serves as a reference paradigm for applying multi-criteria design and experimental methodologies in small to medium-sized home appliances, promoting enhanced grinding quality consistency and operational efficiency. For future product designs, it is recommended to preset the grinding time at 10 s and the burr gap at 0.5 mm to balance particle size stability and output efficiency, supported by precise, real-time data acquisition through integrated smart sensing technologies.

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