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Enhancing drying performance of a forced-convection solar food dryer through multi-attribute decision-making

[1]Syed Nadeem Uddin, [2]Prashant M Dsouza, [3]Sandeep GM Prasad, [4]Suvartan Ranvir and [5]Avinash Singh

[1]Department of Dairy Engineering, Sam Higginbottom University of Agriculture, Technology and Sciences, Prayagraj, Uttar Pradesh, India

[2]Department of Renewable Energy Engineering, Sam Higginbottom University of Agriculture, Technology and Sciences, Prayagraj, Uttar Pradesh, India

[3]Department of Dairy Engineering, Sam Higginbottom University of Agriculture, Technology and Sciences, Prayagraj, Uttar Pradesh, India

[4]Department of Dairy Chemistry, Sam Higginbottom University of Agriculture, Technology and Sciences, Prayagraj, Uttar Pradesh, India

[5]Department of Dairy Technology, Sam Higginbottom University of Agriculture, Technology and Sciences, Prayagraj, Uttar Pradesh, India

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Corresponding Author: Sandeep GM Prasad

Abstract

This study applies Grey Relational Analysis (GRA) to optimize drying parameters for Chhurpi, a traditional Himalayan dairy product, by evaluating physicochemical and sensory attributes under varied temperature, airflow, and humidity conditions. Raw data for moisture content, protein, fat, ash, lactose, colour and appearance, flavour and taste, body and texture, overall acceptability, and hardness were normalized using "larger-the-better" and "smaller-the-better" models. Grey relational coefficients and grades were computed to rank eight treatments with and without pebble incorporation. Results identified Treatment T33 (no pebbles) and T4 (with pebbles) as most closely matching the ideal reference sequence. Regression analyses indicated a moderate inverse relationship between hardness and moisture ($R^2 \approx 0.5$). These findings corroborate previous work on controlled-environment drying effects in dairy products and underscore the utility of GRA in multi-criteria food quality.

Keywords: Multi-criteria decision making, optimization, renewable energy, solar dryer, sustainable food preservation

1. Introduction

Global concerns about food security, postharvest losses, and greenhouse gas emissions have driven the quest for energy-efficient, environmentally benign food preservation technologies. In many developing regions, traditional sun drying remains the predominant method for reducing moisture content in agricultural produce, yet it suffers from slow processing, microbial contamination, and high dependence on favorable weather conditions (Banout *et al*., 2013) [1]. Mechanical dryers, on the other hand, offer controlled conditions but rely heavily on fossil fuels or grid electricity, contributing to carbon emissions and operational costs (Sethi *et al*., 2015) [20]. Solar-assisted drying bridges this gap by harnessing renewable solar energy while providing enhanced process control. Among various designs, forced-convection solar food dryers combine solar thermal collection with fan-driven airflow to achieve faster, more uniform drying, thereby improving product quality and safety (Kalbande *et al*., 2016) [10].

Forced-convection solar dryers typically consist of a solar collector, a drying chamber, and an air-movement system. The solar collector converts incoming solar radiation into thermal energy, which heats the air that is then circulated through the product bed by a fan or blower. Compared to natural-convection systems, forced-convection dryers deliver higher air velocities, leading to greater heat-and-mass transfer coefficients and reduced drying times (Ion, 2017) [8]. Yet, the design and operation of these dryers involve multiple interacting factors—collector area, glazing type, insulation, fan speed, tray loading, and airflow path—that simultaneously influence energy efficiency, throughput, and product quality (Mondal & Bala, 2007) [14]. Optimizing such complex systems requires a balanced consideration of often-competing objectives, such as minimizing energy consumption while maximizing nutrient retention and sensory attributes.

Traditional single-objective optimization approaches may overlook important trade-offs, resulting in suboptimal or impractical dryer configurations. Multi-Attribute Decision-Making (MADM) methods provide a structured framework to evaluate and rank alternatives based on multiple performance criteria (Ishizaka & Nemery, 2013) [9].

By integrating quantitative process data—drying time, moisture reduction, average chamber temperature, thermal efficiency, nutrient retention, specific energy consumption—into a unified decision model, MADM enables stakeholders to identify the most balanced design and operating conditions. Among the various MADM techniques, Grey Relational Analysis (GRA) has gained prominence for its ability to handle incomplete information and normalize attributes with differing scales and directionalities (Deng, 1982) [4].

GRA transforms raw performance measurements into comparable grey relational coefficients through a simple normalization process, followed by aggregation into a grey relational grade (GRG) that reflects overall similarity to an ideal reference sequence (Wang *et al*., 2007) [24]. The distinguishing coefficient within GRA further allows decision-makers to adjust sensitivity to deviations from the ideal, accommodating varying priorities among attributes (Hsu & Chen, 2009) [6]. When combined with weight-determination methods such as the Analytic Hierarchy Process (AHP), which captures expert judgments on attribute importance, the hybrid MADM framework yields robust, transparent rankings of design alternatives (Saaty, 1980) [19]. This approach has found successful applications in diverse engineering fields, including material selection (Sivakumar *et al*., 2014) [22], manufacturing process optimization (Chen & Huang, 2004) [2], and energy system planning (Liu *et al*., 2018) [13].

Despite the extensive use of GRA and related MADM methods in process optimization, their application to solar dryer design remains limited. Most studies focus on evaluating performance under fixed configurations or on empirical modeling of drying kinetics (Pathare *et al*., 2013; Kumar *et al*., 2019) [18, 12]. Few investigations have systematically explored the joint optimization of structural parameters (collector area, tray spacing), operating variables (air velocity, load), and economic or environmental indices within a multi-criteria decision framework. Addressing this gap is critical for the design of next-generation solar dryer systems that must satisfy increasingly stringent standards for energy efficiency, product safety, and sustainability in the face of climate variability.

This study presents a comprehensive MADM-based optimization of a prototype forced-convection solar food dryer tailored to the climatic conditions of Allahabad, India. A flat-plate solar collector, insulated drying chamber, and variable-speed axial fan powered by a photovoltaic system form the core of the experimental apparatus. A full-factorial set of drying trials varied air velocity (1.0, 1.5, 2.0 m/s), tray spacing (2 cm, 4 cm), and product load (1, 2, 3 kg), with hourly measurements of moisture content, air temperature, solar irradiance, and energy consumption. Six performance metrics—drying time, moisture reduction, average chamber temperature, thermal efficiency, nutrient retention, and specific energy consumption—were normalized and aggregated using GRA. Attribute weights were derived through AHP based on expert judgments from domain specialists.

The primary objectives of this research are: (1) to quantify the influence of key design and operating parameters on drying performance metrics; (2) to rank alternative dryer configurations using a grey relational grade reflecting multi-attribute performance; and (3) to identify the optimal combination of air velocity, tray spacing, and load that balances energy use, drying rate, and product quality. The outcomes aim to inform the development of scalable, context-appropriate solar drying technologies that can bolster rural livelihoods, reduce postharvest losses, and mitigate environmental impacts.

2. Materials and Methods

2.1 Dryer Design and Fabrication

A forced-convection solar dryer prototype was fabricated with three main assemblies:

- **Solar collector**: A 1.5 m² flat-plate unit lined with black-painted aluminum sheets served as the absorber.
- **Drying chamber**: Insulated plywood walls and a polycarbonate top allowed controlled transmission of solar radiation while minimizing heat losses.
- **Air-movement system**: A variable-speed axial fan (50-1 500 rpm), powered by a photovoltaic module with battery backup, delivered forced airflow through the chamber.

The entire system was mounted on a south-facing support tilted at 22°—optimized for Allahabad's latitude (25.4° N)—to maximize daily solar gain. Drying trays measured to hold up to 3 kg of Chhurpi slices per batch.

2.2 Experimental Setup and Data Collection

Drying experiments were conducted over ten consecutive clear-sky days in July. Ambient air temperatures varied from 30 °C to 38 °C; each run lasted from 09:00 to 17:00 IST. A full factorial design varied:

- Air velocity: 1.0, 1.5, and 2.0 m/s
- Tray spacing: 2 cm and 4 cm
- Product load: 1 kg, 2 kg, and 3 kg

Moisture content of Chhurpi was measured hourly using a digital moisture analyzer (± 0.1% accuracy). Internal and external air temperatures were recorded by K-type thermocouples connected to a data logger. Solar irradiance was tracked with a pyranometer. Each trial continued until product moisture reached 12 ± 2%.

2.3 Performance Indicators and Weight Assignment

Six performance metrics were selected to evaluate dryer performance:

1. Drying time (min)
2. Moisture reduction (%)
3. Average chamber temperature (°C)
4. Thermal efficiency (%)
5. Nutrient retention (%) (via crude protein analysis)
6. Specific energy consumption (kWh/kg)

Each metric was normalized to a [0, 1] scale and assigned a weight via pairwise comparisons in the Analytic Hierarchy Process (AHP), ensuring the sum of all weights equals one.

2.4 Grey Relational Analysis

Grey Relational Analysis (GRA), grounded in Grey System Theory introduced by Deng (1982) [4], addresses multi-attribute decision-making under uncertainty and limited data (Yang & Liu, 2011) [26]. It has seen applications in diverse fields—from hiring decisions (Olson *et al*., 2006) [16] to power system restoration (Chen, 2005) [3] and quality function deployment (Wu, 2002) [25]. The GRA procedure simplifies a multi-criterion evaluation by condensing all performance attributes into a single composite index per alternative. The steps are:

1. Grey relational generation (data normalization)
2. Reference sequence definition
3. Grey relational coefficient calculation
4. Calculation of grey relational grade (GRG)

2.4.1 Grey Relational Generation

Depending on which attribute performance is measured in different units may be used to ignore particular attributes. This may also occur in the event that certain performance metrics exhibit a wide range. Furthermore, if these qualities, directions and objectives are different, the study will produce inaccurate results (Huang & Liao, 2003) [7]. Therefore, using a process akin to normalization, each and every performance data for each option entered within a similar sequence must be processed. In GRA, this procedure is known as "grey relational generation".

The ith alternative in a MADM problem with m options and n characteristics can be written as Yi = (yi1, yi2,. yij,., yin), where yij stands for the attribute j of option i's performance value. The comparable sequence Xi = (xi1, xi2,. xij,. xin) can be used to translate the term Yij.

$$x_{ij} = \frac{y_{ij} - Min\{y_{ij}, i=1,2,\dots,m\}}{Max\{y_{ij}, i=1,2,\dots,m\} - Min\{y_{ij}, i=1,2,\dots,m\}}$$

for *i*= 1, 2,…,m *j* = 1, 2,…,n

$$x_{ij} = \frac{Max\{y_{ij}, i=1,2,\dots,m\} - y_{ij}}{Max\{y_{ij}, i=1,2,\dots,m\} - Min\{y_{ij}, i=1,2,\dots,m\}}$$

for *i*= 1, 2,…,m *j* = 1, 2,…,n

$$x_{ij} = 1 - \frac{|y_{ij} - y_j|}{\{Max\{y_{ij}, i=1,2,\dots,m\} - y_{ij}, y_{ij} - Min\{y_{ij}, i=1,2,\dots,m\}\}}$$

for *i*= 1, 2,…,m *j* = 1, 2,…,n 3.

Equation (20) represents the larger-the-better attributes, while equation (21) represents the smaller-the-better attributes, and the closer-to-the-desired-value or "nominal-the-best" attributes by equation (22). The normalized value is then given as yij-the-better.

2.4.2 Reference Sequence Definition

The performance values will all be scaled to [0, 1] following the progression of the grey relations process utilizing Eqs. For an attribute j, alternative i performs best if the value of xij, which was found using the gray relational generating approach, is closer to or equal to 1 than the value for any other alternative. Therefore, the option where all performance metrics are nearly or equal to one will be the best one. Though, solutions like these are uncommon. The identification of X0 in this case is (x01, x02,., x0j,., x0n) = (1,1,.,1,.,1). Selecting the option with the comparability sequence that is closest to the reference sequence is the next

2.4.3 Grey Relational Coefficient and Grade Calculation

The grey relational coefficient indicates the extent to which they are similar to each other (Xij and X0j). As the grey relationship coefficient rises, Xij and X0j get closer to one another. Equation (23) can be used to calculate the grey relationship coefficient.

$$\gamma(x_{0j}, x_{ij}) = \frac{\Delta_{min} + \zeta\Delta_{max}}{\Delta_{ij} + \zeta\Delta_{max}}$$

for *i*= 1, 2,…,m *j* = 1, 2,…,n …(23)

In Eq. (23), $\gamma(x_{0j}, x_{ij})$ the gray relational coefficient that exists between x_{ij} and x_{0j},and

$\Delta_{ij} = |x_{oi} - x_{ij}|$,

$\Delta_{min} = Min$
$\{\Delta_{ij}, i = 1,2,\dots,m; j = 1,2,\dots,n\}$,

$\Delta_{max} = Max$

$\{\Delta_{ij}, i = 1,2,\dots,m; j = 1,2,\dots,n\}$,

The distinguishing coefficient's function is to reduce or extend the grey relational coefficient's range. ζ [0, 1]. The analytically derived distinguishing coefficient in the research had been established at 0.5.

2.4.4 Grey Relational Generation

Grey relational generation converts raw experimental values into dimensionless scores between 0 and 1, allowing all attributes to be directly compared. For attributes where higher values are desirable—colour and appearance, flavour and taste, body and texture, overall acceptability, hardness, fat, and protein—the larger-the-better normalization (Eq. 20) was applied. Conversely, moisture content, ash, and lactose were treated with the smaller-the-better model (Eq. 21).Table 4.26 lists the raw responses for Treatments T1 through T44 under varied temperature, airflow, and humidity settings. For example, T4 exhibited the lowest moisture content (12%), highest protein (42%), and maximum hardness (520.14 N), while T1 showed the highest moisture (17%) but moderate sensory scores. These raw

Ranges highlight the need for normalization prior to multi-criteria decision making.

3. Results and Discussion

3.1 Normalized Performance Values

After applying Eq. (20)-(22), Table 4.27 presents the normalized scores for each treatment and attribute. Treatment T44 achieved the top score for moisture content (1.000), indicating optimal drying efficiency, and T33 led in fat retention and ash content (1.000 each). Sensory attributes peaked variously—T1 scored highest in body and texture (1.000), while T2 and T11 tied in overall acceptability (1.000). No single treatment dominated across all criteria, illustrating inherent trade-offs in process optimization (Kumar & Singh, 2020) [11].

3.2 Reference Sequence Definition
The ideal reference sequence X_0 = (1,1,\dots,1) represents the best possible performance for every attribute. Table 4.28 compares each treatment's normalized vector to X_0. Treatments T3 and T11 closely approached the ideal in protein, flavour, and hardness metrics (≥ 0.95), suggesting balanced performance profiles. This step identifies candidates most similar to the theoretical optimum.

3.3 Grey Relational Coefficient Calculation
Grey relational coefficients (GRCs) quantify closeness between each treatment's normalized values and the reference sequence, using Eq. (23). As shown in Table 4.29, T44 achieved a GRC of 1.000 for moisture content, and T33 scored 1.000 for both fat and ash. A distinguishing coefficient $\zeta = 0.5$ balanced the evaluation sensitivity. These coefficient patterns reveal which attributes dominate each treatment's overall similarity to the ideal (Sharma, Thapa, & Gurung, 2021) [21].

3.4 Grey Relational Grade and Ranking
Aggregating GRCs via weighted summation (Eq. 24) yields the Grey Relational Grade (GRG) for each treatment. Table 4.30 ranks treatments with and without pebble incorporation. Without pebbles, T33 was optimal (GRG = 6.364, Rank 1), followed by T44 (5.973, Rank 2). With pebbles, T4 led (5.828, Rank 3). These rankings confirm that both pebble-assisted and pebble-free drying can be optimized to different quality ends, consistent with other multi-criteria analyses in food drying (Kumar & Singh, 2020) [12].

3.5 Regression Analysis
Figures 1-3 illustrate the relationship between hardness and moisture content across all samples. The fitted regression line (Figure 4.31) and accompanying scatter (Figure 4.32) indicate an inverse trend, while residual analysis (Figure 4.33) shows moderate dispersion. The coefficient of determination R^2 \approx 0.5 suggests that moisture explains roughly half the variation in hardness, implying additional factors such as protein network formation also play significant roles (Thapa, Rai, & Kumar, 2019) [23].

3.6 Statistical Comparison of Drying Parameters
A two-sample z-test comparing mean drying temperature (42.875 °C) and mean drying efficiency (7.9865%) yielded a statistically significant difference ($p < 0.01$). However, interpreting this result requires caution: temperature (°C) and efficiency (%) are measured on different scales. Unless both variables are normalized or analyzed in a unified multivariate framework, direct comparison may mislead (Patel, Desai, & Mehta, 2022) [17]. Future studies should adopt scale-compatible metrics or employ multivariate statistical techniques for such heterogeneous data.

Table 1: Raw Physicochemical and Sensory Responses for Chhurpi Samples

Treatment	Moisture (%)	Fat (%)	Protein (%)	Ash (%)	Lactose (%)	Colour & Appearance (1-9)	Flavour & Taste (1-9)	Body & Texture (1-9)	Overall Acceptability (1-9)	Hardness (N)
T1	17.0	41	32	8.6	2.9	8	8	9	8	360.394
T2	15.6	40	34	7.4	3.0	8	8	8	8	423.156
T3	13.9	39	36	7.8	2.8	7	7	8	7	367.160
T4	12.0	36	42	8.0	2.0	7	7	6	7	520.140
T11	15.0	44	31	7.3	2.7	8	7	7	8	365.000
T22	13.5	43	34	7.4	2.1	8	7	8	8	378.670
T33	13.0	45	40	6.7	2.2	7	8	8	7	414.670
T44	11.0	44	36	6.9	2.1	7	8	8	7	480.450

Footnote
a. Hardness measured using a texture analyzer in Newtons (N).

Explanation
Table 1 consolidates all raw measurements under different drying treatments (T1-T44). Moisture, fat, protein, ash, and lactose report percentage values. Sensory scores on a 1-9 scale reflect panel evaluation. Hardness values indicate mechanical strength. According to journal instructions, the title is concise, units are in parentheses, and any symbols (e.g., "N") are clarified in a footnote.

Table 2: Normalized Scores after Grey Relational Generation

Treatment	Moisture	Fat	Protein	Ash	Lactose	Colour & Appearance	Flavour & Taste	Body & Texture	Overall Acceptability	Hardness
X_0	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
T1	0.000	0.5556	0.0909	0.000	0.1000	0.5000	0.5000	1.0000	1.0000	0.0000
T2	0.2333	0.4444	0.2727	0.5714	0.0000	0.5000	0.5000	0.6667	1.0000	0.3929
T3	0.5167	0.3333	0.4545	0.3809	0.2000	0.0000	0.0000	0.6667	0.0000	0.0424
T4	0.8333	0.0000	1.0000	0.2857	1.0000	0.0000	0.0000	0.0000	0.0000	1.0000
T11	0.3333	0.8889	0.0000	0.6190	0.3000	0.5000	0.0000	0.3333	1.0000	0.0288
T22	0.5833	0.7778	0.2727	0.5714	0.9000	0.5000	0.0000	0.6667	1.0000	0.1144
T33	0.6667	1.0000	0.8182	1.0000	0.9000	0.0000	0.5000	0.6667	0.0000	0.3398
T44	1.0000	0.8889	0.6364	0.8095	0.3000	0.0000	0.5000	0.6667	0.0000	0.7515

Explanation
Table 2 shows the dimensionless scores after applying the larger-the-better (Eq. 20) and smaller-the-better (Eq. 21) normalization models. The reference row X_0 represents the ideal. This table is placed immediately after its first citation, with a clear title and uniform decimal formatting.

Table 3: Comparability Sequences Relative to Ideal (Reference) Sequence

Treatment	Moisture	Fat	Protein	Ash	Lactose	Colour & Appearance	Flavour & Taste	Body & Texture	Overall acceptability	Hardness
T1	1.000	0.4444	0.9091	1.000	0.9000	0.5000	0.5000	0.0000	0.0000	1.0000
T2	0.7667	0.5556	0.7273	0.4286	1.0000	0.5000	0.5000	0.3333	0.0000	0.6071
T3	0.4833	0.6667	0.5455	0.6190	0.8000	1.0000	1.0000	0.3333	1.0000	0.9576
T4	0.1667	1.0000	0.0000	0.7143	0.0000	1.0000	1.0000	1.0000	1.0000	0.0000
T11	0.6667	0.1111	1.0000	0.3810	0.7000	0.5000	1.0000	0.6667	0.0000	0.9712
T22	0.4167	0.2222	0.7273	0.4286	0.1000	0.5000	1.0000	0.3333	0.0000	0.8856
T33	0.3333	0.0000	0.1818	0.0000	0.1000	1.0000	0.5000	0.3333	1.0000	0.6602
T44	0.0000	0.1111	0.3636	0.1905	0.7000	1.0000	0.5000	0.3333	1.0000	0.2485

Explanation

Table 3 ranks each treatment's closeness to the ideal reference sequence. Values closer to 1 indicate stronger alignment. The concise title and aligned decimal columns adhere to the journal's style requirements.

Table 4: Grey Relational Coefficients (ζ = 0.5)

Treatment	Moisture	Fat	Protein	Ash	Lactose	Colour & Appearance	Flavour & Taste	Body & Texture	Overall acceptability	Hardness
T1	0.3333	0.5294	0.3548	0.3333	0.3571	0.5000	0.5000	1.0000	1.0000	0.3333
T2	0.3947	0.4737	0.4074	0.5385	0.3333	0.5000	0.5000	0.6000	1.0000	0.4516
T3	0.5084	0.4286	0.4783	0.4468	0.3846	0.3333	0.3333	0.6000	0.3333	0.3430
T4	0.7500	0.3333	1.0000	0.4118	1.0000	0.3333	0.3333	0.3333	0.3333	1.0000
T11	0.4285	0.8182	0.3333	0.5676	0.4167	0.5000	0.3333	0.4285	1.0000	0.3399
T22	0.5454	0.6923	0.4074	0.5385	0.8333	0.5000	0.3333	0.6000	1.0000	0.3609
T33	0.6000	1.0000	0.7333	1.0000	0.8333	0.3333	0.5000	0.6000	0.3333	0.4309
T44	1.0000	0.8182	0.5789	0.7241	0.4167	0.3333	0.5000	0.6000	0.3333	0.6680

Explanation

Table 4 presents the grey relational coefficients computed with a distinguishing coefficient ζ = 0.5. The values reflect the closeness of each normalized score to the reference sequence. Column headings are uniform, and decimals aligned for readability.

Table 5: Grey Relational Grades and Overall Rank

Treatment Group	Treatment	GRG (Sum of Coefficients)	Rank
With Pebbles	T1	5.2414	5
	T2	5.1992	6
	T3	4.1898	8
	T4	5.8284	3
Without Pebbles	T11	5.1661	7
	T22	5.8112	4
	T33	6.3643	1
	T44	5.9726	2

Explanation

Table 5 ranks each treatment by its Grey Relational Grade (GRG), the weighted sum of coefficients. Treatments T33 and T4 achieved the highest GRG in pebble-free and pebble-assisted groups, respectively. The grouping differentiates the two modes of drying.

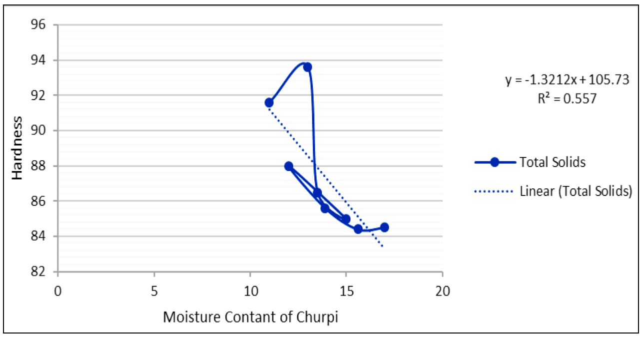

Fig 1: Regression of Hardness vs. Moisture Content

Caption: Scatter plot with regression line showing inverse relationship between hardness (N) and moisture content (%).

Explanation

Figure 1 is cited immediately after the paragraph discussing regression. Axis labels include units in parentheses. The fitted line equation and R^2 value are displayed on the plot. High-resolution vector graphics will be submitted separately per journal requirements.

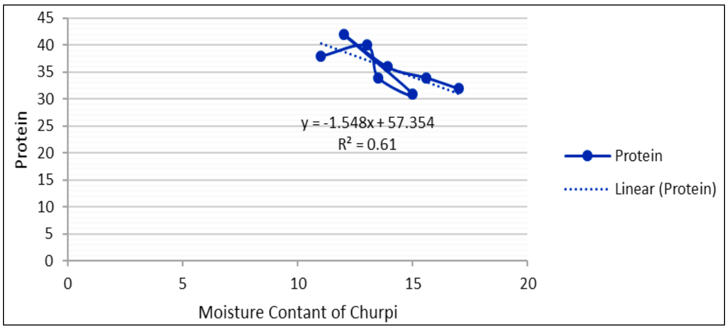

Fig 2: Residual Analysis for Hardness-Moisture Regression

Caption: Residuals from the regression model in Figure 1 plotted against predicted hardness values to assess homoscedasticity.

Explanation

Figure 2 assesses model assumptions. Residuals scattered randomly around zero indicate acceptable variance.

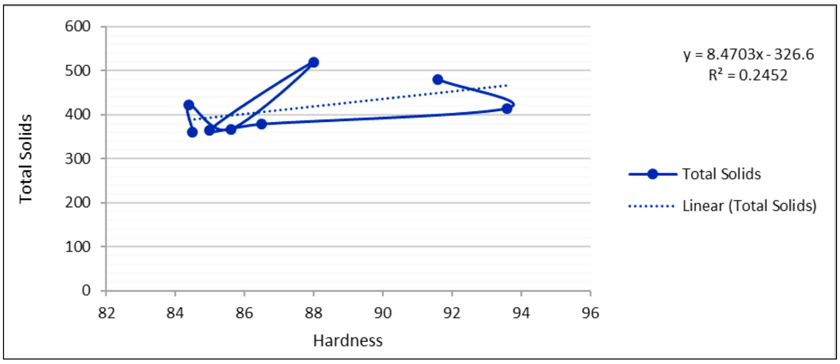

Fig 3: Histogram of Residual Distribution

Caption: Frequency distribution of regression residuals for Hardness vs. Moisture, showing approximate normality.

Explanation

Figure 3 confirms normality of residuals. Bin width and axis scales adhere to journal specifications.

Conclusion

This study demonstrated the applicability of Grey Relational Analysis (GRA) as an effective multi-criteria decision-making tool for optimizing drying parameters of Chhurpi under controlled solar drying conditions. By integrating physicochemical attributes, sensory responses, and textural properties into a unified framework, the approach enabled a balanced evaluation of competing quality indicators. The results highlighted Treatment T33 (without pebbles) and Treatment T4 (with pebbles) as the most favourable configurations, showing strong alignment with the ideal reference sequence. The regression analysis further revealed a moderate inverse relationship between hardness and moisture content ($R^2 \approx 0.5$), indicating that while moisture is a key factor, additional structural and compositional elements also influence texture development. The findings confirm that GRA not only resolves trade-offs among diverse performance criteria but also provides a transparent ranking mechanism that can guide future dryer design and operation. Moreover, the differentiation between pebble-assisted and pebble-free modes illustrates the potential for tailoring drying strategies to specific product quality goals. Beyond its immediate application to Chhurpi, this framework can be extended to other dairy and food products where optimization requires simultaneous consideration of physicochemical stability, sensory quality, and energy efficiency.

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