Application of Fuzzy Tahani and TOPSIS Methods for Personalizing the Coffee Brewing Process According to Consumer Taste Preferences

Adhitya Setiawan [1*], Puji Subekti [2]

[1, 2] *Informatics Engineering Study Program, Faculty of Technology and Design, Institut Teknologi dan Bisnis Asia Malang, Jl. Soekarno-Hatta No. 1A, Malang, East Java, Indonesia*

Keywords

Coffee brewing; Fuzzy Tahani; TOPSIS; Decision Support System; Brew Strength; Extraction Yield; TDS.

Correspondence Email:

puji.subekti@asia.ac.id

Abstract

Coffee brewing quality is determined by parameters such as bean density, water temperature, grind size, and brew ratio, each influencing the final brew strength classified as light, medium, or strong. Variations in these factors make it difficult to achieve consistent extraction outcomes through sensory evaluation alone. To address this limitation, a web-based decision support system was developed by integrating the Fuzzy Tahani inference model with the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) ranking method. The system evaluates 1,309 parameter combinations derived from empirical ranges of density (350–450 kg/m^3), temperature (90–96 °C), grind size (500–1300 µm), and brew ratio (1:12–1:18). Three quantitative suitability functions measure density–temperature, grind–strength, and ratio–strength alignment, while a fourth quantifies fuzzy rule compatibility. These functions are aggregated using TOPSIS to rank valid alternatives and determine the optimal configurations for each brew-strength category. Validation through controlled pour-over experiments confirms the computational model: Total Dissolved Solids (TDS) decrease proportionally with increasing bean density, whereas Extraction Yield (EY) remains stable within the ideal 18–22 % range as defined by the Coffee Brewing Control Chart. The integration of Fuzzy Tahani and TOPSIS bridges linguistic reasoning with quantitative evaluation, yielding reproducible recommendations for consistent and precise coffee-brewing control.

1. Introduction

Coffee represents one of Indonesia's most significant agricultural commodities, playing a crucial role not only in supporting national economic development but also in shaping the nation's cultural identity(Gabriel & Lubis, 2025); (Afrianto et al., 2024);(Wahdiniwaty et al., 2025). As a leading global coffee producer, Indonesia is widely recognized for its unique regional flavor diversity, with notable origins such as Gayo, Toraja, and Kintamani. Over the past decade, the emergence of the specialty coffee movement has transformed consumer behavior from casual consumption to a more discerning appreciation of sensory attributes, including flavor nuances, aromatic complexity, and precision in brewing techniques (SCA, 2022). This shift in consumer expectations has intensified the demand for both consistency and personalization in coffee preparation. Nevertheless, maintaining uniform quality remains a persistent challenge due to fluctuations in brewing variables, variations in bean properties, and the subjective nature of individual taste preferences. These challenges underscore the importance of developing intelligent decision-support systems capable of simultaneously analyzing multiple parameters to achieve reproducible and user-tailored brewing results.

Along with this shift, preferences for brew strength have become increasingly diverse. The Specialty Coffee Association (SCA, 2022) notes that parameters such as water temperature, coffee-to-water ratio, grind size, and bean density are critical factors influencing both the sensory intensity and overall brewing quality. Meanwhile, (Guinard et al., 2023a) emphasize that the interaction between these parameters determines the perception of strength, taste balance, and aroma harmony. Despite the growing understanding of these relationships, achieving consistent brewing results remains difficult due to the variability of technical parameters and the subjectivity involved in sensory evaluation (Lee et al., 2023). Therefore, the use of data-driven decision-support systems (DSS) is needed to provide objective and reproducible recommendations for coffee brewing optimization. This subjectivity poses a significant challenge for personalization, as individual differences in sensory perception make it difficult to translate qualitative taste preferences into precise, quantifiable brewing parameters. Consequently, manual adjustments often fail to consistently reflect the intended flavor profile for each consumer(Wahdiniwaty et al., 2025).

Research in computational decision-making has shown that fuzzy logic can effectively address problems involving uncertainty and qualitative parameters. (Mallu & Saharuddin, 2023) compared the Fuzzy Tahani and WASPAS methods, concluding that Fuzzy Tahani offers better flexibility in managing linguistic and multi-criteria data. For numerical ranking and evaluation, (Chaube et al., 2024) reviewed the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method, highlighting its precision and reliability for complex multi-criteria analysis. Furthermore, (Barry Nuqoba et al., 2025) developed an integrated fuzzy–TOPSIS model that improved ranking transparency and interpretability by combining linguistic reasoning with numerical scoring, enhancing the overall consistency of decision-making outcomes.

The application of these hybrid approaches has also expanded to web-based systems, enabling real-time analysis and accessibility. (Chang et al., 2020) implemented a fuzzy DSS using the Python–Django framework, demonstrating that inference mechanisms can be effectively embedded within web architectures. Similarly, (Mahmoudian Azar Sharabiani & Mousavi, 2023) applied fuzzy logic with Pythagorean TOPSIS to improve user interaction and analytical clarity in web-based DSS environments, while (Bhumula & G. N, 2024) automated ranking computations through a Python-based CRITIC–TOPSIS integration for performance evaluation.

This study presents the development of a web-based decision-support system built with Django (Python) to determine optimal coffee-brewing parameters according to brew-strength preferences (light, medium, and strong). The proposed model integrates the Fuzzy Tahani inference approach for qualitative reasoning with the TOPSIS ranking method for quantitative evaluation, aiming to improve the accuracy, consistency, and reproducibility of brewing analysis through intelligent automation. While previous research has mainly examined individual factors such as temperature, grind size, or extraction time, studies integrating bean density with automated consumer-based personalization remain limited. To address this gap, the present work combines density-dependent parameters and preference variables within a unified multi-criteria framework, enabling adaptive recommendations through the integration of empirical data and fuzzy decision modeling.

1.1 Literature Review

Recent research in coffee extraction has emphasized the influence of physical parameters and process control on both sensory perception and chemical yield. The Specialty Coffee Association (SCA, 2022)) introduced the Coffee Brewing Control Chart, which defines the relationship between Total Dissolved Solids (TDS) and Extraction Yield (EY) as key indicators of brew strength and quality balance. According to SCA standards, optimal coffee extraction typically falls within the range of 18–22% EY and 1.15–1.55% TDS for filter brewing, serving as a benchmark for researchers analyzing brewing consistency and beverage sensory profiles.

Building upon this foundation, (Schmieder et al., 2023) systematically investigated the effects of flow rate, particle size, and temperature on espresso extraction kinetics, revealing that water flow rate and grind fineness jointly determine solute mass transfer and extraction efficiency. (Angeloni et al., 2023) analyzed how ground coffee particle-size distribution affects beverage composition and aroma development, demonstrating that finer and more uniform particles enhance the extraction of phenolic and aromatic compounds. (Dong et al., 2024) further demonstrated that microstructural differences in coffee beans influence sorption behavior and water penetration, with denser beans exhibiting slower hydration and solute diffusion rates. Similarly, (Xu et al., 2023) reported that bean density varies with agricultural and shading systems, which subsequently affect roasting behavior and extractive potential. These findings align with (Licata, 2019), who emphasizes that denser beans require higher brewing temperatures to achieve optimal solubility, linking density and temperature as key interacting variables in extraction dynamics.

Beyond conventional brewing methods, novel extraction approaches have also gained attention. (Liu et al., 2024) introduced a dual-frequency ultrasonic-assisted extraction process for cold brew coffee that accelerates mass transfer while maintaining desirable flavor and chemical balance. (Várady et al., 2022) examined how TDS, EY, grind size, and brewing method affect antioxidant activity in fermented specialty coffee, finding that finer grinding and higher extraction yield increase antioxidant capacity. (Guinard et al., 2023b) expanded on SCA's Brewing Control Chart by mapping sensory attributes, brew strength, and extraction yield to consumer preferences, providing a modernized empirical reference for defining optimum brewing ratios and sensory balance.

In parallel with empirical studies, computational intelligence techniques have been increasingly applied to model the complex interactions among brewing parameters(Aminoroaya et al., 2025) proposed an interval-valued Fuzzy–TOPSIS framework that enhances decision-ranking accuracy under uncertainty. (Nguyen et al., 2021) developed a two-phase fuzzy decision-making model (FAHP–VIKOR) for the coffee supply chain, demonstrating the relevance of fuzzy logic in optimizing multi-criteria processes within the coffee industry. (Bilalovic et al., 2020) combined Fuzzy-AHP and Fuzzy-MABAC for traffic-risk analysis, illustrating the robustness of hybrid fuzzy systems in handling uncertain decision structures. Similarly, (Meng et al., 2023) implemented a Python-based fuzzy decision-support system (DSS) capable of real-time process optimization, underscoring the potential of adaptive, web-enabled fuzzy frameworks for continuous process control.

Collectively, these studies demonstrate that integrating empirical coffee-brewing data with fuzzy logic and TOPSIS-based modeling produces decision-support systems capable of translating linguistic assessments (e.g., light, medium, strong) into quantifiable parameters. Such integration enhances objectivity, reproducibility, and adaptability in coffee-brewing optimization and provides a strong theoretical foundation for web-based decision-support systems that ensure consistent and precise brewing control.

2. Research Methods

2.1 Sampling

The analytical unit in this study is a combination of coffee-brewing parameters representing experimental conditions of four main input variables: bean density (d), water temperature (t), grind size (g), and brew ratio (r). The single output variable corresponds to the brew-strength profile (s), categorized as strong, medium, or light.

Since density and temperature have a fixed one-to-one correspondence, each pair $(d, t)$is treated as a single entity in the data-combination process. Mathematically, the complete set of alternatives is expressed as

$$A = \{a_i = (d_i, t_i, g_i, r_i, s_i)\}_{i=1}^{N}, \tag{1}$$

where N denotes the total number of alternative brewing combinations evaluated using the Fuzzy–TOPSIS model.

2.2 Data Collection

The dataset was generated by forming all possible combinations of the input variables according to empirically defined ranges, as shown in Table 2.1.

Table 2.1. Variable Sets and Value Ranges

Variable	Value Set	Description
Density (d)	350, 360, 370, 380, 390, 400, 410, 420, 430, 440, 450	Coffee bean density (kg/m^3)
Temperature (t)	90, 91, 91, 92, 92, 93, 93, 94, 95, 95, 96	Fixed temperature corresponding to each density
Grind size (g)	500–1300 μm (increments of 50 μm)	Ground coffee particle size
Brew ratio (r)	1:12–1:18	Coffee-to-water ratio
Strength profile (s)	strong, medium, light	Brew-strength categories

The fixed relationship between density and temperature was defined as
(350,90), (360,91), (370,91), (380,92), (390,92), (400,93), (410,93), (420,94), (430,95), (440,95), (450,96).

With eleven fixed (d, t) pairs, seventeen grind-size levels, and seven brew ratios, the total number of parameter combinations was calculated as

$$N = |(d,t)| \times |G| \times |R| = 11 \times 17 \times 7 = 1{,}309. \tag{2}$$

Thus, a total of 1,309 combinations were generated as the dataset for the Fuzzy–TOPSIS decision-support model.

2.3 Measures

Four quantitative suitability functions were designed to evaluate the alignment of each parameter set with its target brew-strength category (light, medium, or strong). All functions were normalized within the interval [0,1].

(1) Density–Temperature Compatibility

$$T_{\text{ideal}}(d) = 90 + \frac{(d-350)}{(450-350)}(96-90), f_1(d,t) = \max\left(0, 1 - \frac{|t - T_{\text{ideal}}(d)|}{3}\right). \tag{3}$$

(2) Grind-Size Compatibility

$$G_{\text{ideal}}(d,s) = \begin{cases} 1000 - \dfrac{d-350}{100}(1000-800), & s = \text{light} \\ 900 - \dfrac{d-350}{100}(900-750), & s = \text{medium} \\ 800 - \dfrac{d-350}{100}(800-700), & s = \text{strong} \end{cases}$$

$$f_2(d,g,s) = \max\left(0, 1 - \frac{|g - G_{\text{ideal}}(d,s)|}{200}\right). \tag{4}$$

(3) Brew-Ratio Compatibility

$$R_{\text{ideal}}(d,s)=\begin{cases}13+\frac{d-350}{100}(18-13), & s=\text{light}\\ 12+\frac{d-350}{100}(17-12), & s=\text{medium}\\ 12+\frac{d-350}{100}(16-12), & s=\text{strong}\end{cases}$$

$$f_3(d,r,s)=\max\left(0,1-\frac{|r-R_{\text{ideal}}(d,s)|}{2}\right). \tag{5}$$

(4) Fuzzy Rule Compatibility

$$f_4(a_i)=\text{compatibility}(a_i)\in[0,1]. \tag{6}$$

Although f_4 is not a physical parameter, it represents the logical consistency of fuzzy inference and contributes 20% of the total weight in the TOPSIS ranking process to integrate linguistic reasoning with numerical evaluation.

2.4 Procedure and Model Formulation

2.4.1 Fuzzy Tahani Model

The four input variables (d,t,g,r) were transformed into linguistic values using a triangular membership function defined as

$$\mu_A(x)=\begin{cases}1, & a_{\min}\le x\le a_{\max}\\ \max\left(0,0.7-\frac{\Delta(x,[a_{\min},a_{\max}])}{100}\right), & \text{otherwise}\end{cases} \tag{7}$$

where $\Delta(x,[a_{\min},a_{\max}])=\min(|x-a_{\min}|,|x-a_{\max}|)$.

The linguistic variable sets used in the model are summarized below.

Table 2.2. Fuzzy Rule Base

Variable	Linguistic Sets
Density (d)	Very Low (350–370), Low (370–390), Medium (390–420), High (420–440), Very High (440–450)
Temperature (t)	Low (90–91 °C), Medium (91–93 °C), High (93–96 °C)
Grind Size (g)	Very Fine (500–700 µm), Fine (650–750 µm), Medium (750–900 µm), Coarse (900–1000 µm), Very Coarse (1000–1300 µm)
Brew Ratio (r)	Very Short (1:12–1:13), Short (1:13–1:14), Medium (1:14–1:16), Long (1:16–1:17), Very Long (1:17–1:18)

The fuzzy rule base consists of 15 rules that map combinations of density, temperature, grind size, and brew ratio to corresponding strength categories (strong, medium, light), as presented in Table 2.3.

Table 2.3. Fuzzy Rule Base

No	Density	Temperature	Grind Size	Brew Ratio	Strength
1	Very Low	Low	Medium	Very Short	Strong
2	Low	Medium	Medium	Very Short	Strong
3	Medium	Medium	Fine	Short	Strong
4	High	High	Very Fine	Medium	Strong
5	Very High	High	Very Fine	Medium	Strong
6	Very Low	Low	Coarse	Very Short	Medium
7	Low	Medium	Medium	Short	Medium
8	Medium	Medium	Medium	Medium	Medium
9	High	High	Fine	Long	Medium
10	Very High	High	Fine	Long	Medium
11	Very Low	Low	Very Coarse	Short	Light
12	Low	Medium	Coarse	Medium	Light

13	Medium	Medium	Coarse	Long	Light
14	High	High	Medium	Very Long	Light
15	Very High	High	Medium	Very Long	Light

Rule Evaluation and Integration

The compatibility of each brewing combination $a_i = (d_i, t_i, g_i, r_i)$is calculated using the geometric mean:

$$C_k(a_i) = \Big(\prod_{v \in \{d,t,g,r\}} \mu_{L_v^{(k)}}(v_i)\Big)^{1/m_k}. \tag{8}$$

The maximum compatibility value for each strength category is obtained as

$$\text{compatibility}(a_i) = \max_{k:\text{strength}(k)=s} C_k(a_i), \tag{9}$$

and a combination is considered valid if

$$\text{compatibility}(a_i) > \tau, \text{where } \tau = 0.1. \tag{10}$$

The final compatibility value becomes $f_4(a_i)$, which is incorporated into the TOPSIS evaluation.

2.4.2 TOPSIS Ranking

Each valid alternative $A^{\text{valid}}$was evaluated using four benefit-type criteria $\{f_1, f_2, f_3, f_4\}$with the weight vector $w = (0.15, 0.30, 0.35, 0.20)$. The normalization and weighting process is given by

$$v_{ij} = \frac{x_{ij}}{\sqrt{\sum_i x_{ij}^2}}, y_{ij} = w_j v_{ij}. \tag{11}$$

The positive and negative ideal solutions are computed as

$$y_j^+ = \max_i y_{ij}, y_j^- = \min_i y_{ij}. \tag{12}$$

The separation distances and closeness coefficient are then calculated as

$$S_i^+ = \sqrt{\sum_j (y_{ij} - y_j^+)^2}, S_i^- = \sqrt{\sum_j (y_{ij} - y_j^-)^2}, CC_i = \frac{S_i^-}{S_i^+ + S_i^-}. \tag{13}$$

Alternatives with the highest CC_ivalues represent the most optimal brewing parameters for each brew-strength category.

2.4.3 Computational Flow

The model development followed a structured sequence:

1. Define fixed (d, t)pairs based on the density–temperature relationship.
2. Generate all possible (d, t, g, r)combinations, resulting in 1,309 alternatives.
3. Evaluate fuzzy validity using the Fuzzy Tahani model.
4. Apply TOPSIS to rank valid combinations using $f_1$through f_4.
5. Select the top five configurations for each strength category (strong, medium, and light).

This sequence ensures a systematic transition from data generation to parameter optimization.

2.5 Experimental Validation: TDS and Extraction Yield Measurement

Experimental validation was performed using a digital coffee refractometer to quantify Total Dissolved Solids (TDS) and Extraction Yield (EY), representing brew strength and extraction efficiency, respectively. These metrics were employed to evaluate the accuracy of the computational model and to determine whether each sample achieved the optimal extraction range. The measurements were calculated using the following relationships:

$$\text{TDS} = \frac{R}{CF}, \text{EY} = \frac{\text{TDS} \times M_{\text{brew}}}{M_{\text{coffee}}}, \tag{14}$$

where R is the refractometer reading (%), CF is the correction factor, M_{brew} is the mass of brewed beverage (g), and M_{coffee} is the mass of ground coffee (g). The calculated TDS and EY values were plotted on the Coffee Brewing Control Chart to classify the extraction results as under-extracted, ideal, or over-extracted. The computational model was considered validated when experimental outcomes were located within the ideal extraction zone, defined by TDS values between 1.25–1.55% and EY values between 18–22%.

2.6 Experimental Setup and Brewing Procedure

The brewing experiments were performed using a controlled pour-over setup designed to maintain consistent time and flow across all density levels. Brew density (D) was calculated as

$$D = \frac{\text{Mass of coffee (g)}}{\text{Brewed volume (L)}}. \tag{15}$$

Each brewing experiment utilized a fixed coffee dose of 15 g. Grinding was performed using a 1Zpresso ZP6 Special hand grinder calibrated to approximately 22 µm per click. The brewing process employed a Hario Switch 02 dripper with manual valve control, assisted by a Hario Drip Assist to maintain a stable flow—using the inner ring for the first pour and the outer ring for the second. A Hario paper filter 01 was applied in conjunction with a Fellow Stagg EKG kettle capable of maintaining temperature precision within ±1 °C. The water source used was Cleo purified water with a total dissolved solids (TDS) level of 8–9 ppm. Measurements of TDS were obtained using a digital coffee refractometer.

The brewing process consisted of two primary pouring phases. The first pour, accounting for 30% of the total volume, began at 00:00 seconds with the valve closed and was opened between 00:15 and 00:20 seconds depending on bean density—lower-density samples initiated earlier. The valve was subsequently closed between 00:30 and 00:35 seconds to allow pre-extraction. The second pour, representing the remaining 70%, commenced at approximately 00:30–00:35 seconds, with the valve reopened around 00:55 seconds until drawdown completed between 01:20 and 01:55 minutes. Higher-density beans (≥410 kg/m^3) required longer total brewing durations of approximately 01:55 minutes, while lower-density beans (≤380 kg/m^3) completed extraction in about 01:20 minutes. For measurement consistency, TDS readings were taken once the beverage cooled to 25–35 °C. Each sample was analyzed three times sequentially, and the third reading was adopted as the final TDS value to ensure accuracy.

3. Result and Discussion

3.1 Results

In line with the research objectives, this section reports the outcomes of pour-over experiments conducted across bean densities ranging from 350 to 450 kg/m^3. Each density level was evaluated under three brew-strength categories (strong, medium, and light). The measured variables included Total Dissolved Solids (TDS), beverage yield (final mass), and Extraction Yield (EY), following the procedures described in Sections 2.5 and 2.6. The complete brewing results obtained from these experiments are presented in Table 3.1, which summarizes the relationship between bean density, brew strength, TDS, Yield and extraction performance.

Table 3.1. Brew Strength Results Across Bean Density Levels

Density (kg/m^3)	Strength	TDS (%)	Yield (g)	EY (%)
350	Strong	2.38	125	19.83
	Medium	1.90	145	18.37
	Light	1.77	155	18.29
360	Strong	1.93	148	19.04
	Medium	1.83	147	17.93
	Light	1.73	163	18.80
370	Strong	1.93	148	19.04
	Medium	1.83	147	17.93
	Light	1.73	163	18.80
380	Strong	1.73	160	18.45

	Medium	1.61	168	18.03
	Light	1.50	180	18.00
390	Strong	1.61	175	18.78
	Medium	1.50	180	18.00
	Light	1.46	186	18.10
400	Strong	1.74	173	20.07
	Medium	1.51	183	18.42
	Light	1.42	201	19.03
410	Strong	1.64	177	19.35
	Medium	1.56	186	19.34
	Light	1.45	201	19.43
420	Strong	1.55	184	19.01
	Medium	1.43	195	18.59
	Light	1.31	214	18.69
430	Strong	1.54	186	19.10
	Medium	1.41	202	18.99
	Light	1.31	217	18.95
440	Strong	1.42	201	19.03
	Medium	1.33	218	19.33
	Light	1.28	227	19.37
450	Strong	1.48	200	19.73
	Medium	1.34	216	19.30
	Light	1.24	233	19.26

The pour-over experiments conducted across bean density levels ranging from 350 to 450 kg/m^3 revealed a consistent relationship among bean density, brew strength, and extraction parameters, including Total Dissolved Solids (TDS), yield, and Extraction Yield (EY). As shown in Table 3.1, an inverse correlation was observed between bean density and TDS values, while a positive correlation emerged between bean density and yield. This phenomenon indicates that as bean density increases, the concentration of dissolved solids in the brewed beverage tends to decrease, whereas the mass or volume of the extracted beverage increases. Overall, EY values remained within a stable range of 18–20%, suggesting that the extraction efficiency was largely maintained across all density variations tested.

The decrease in TDS values with increasing bean density can be interpreted as a result of changes in water flow characteristics during the brewing process. Coffee beans with higher density tend to produce a more compact and tightly packed coffee bed, which slows down the infiltration rate of water through the extraction medium. This condition limits the dissolution of solid compounds, resulting in fewer dissolved substances being extracted and consequently lower TDS values. However, this effect is compensated by an increase in yield, as a greater volume of water passes through and is absorbed by the coffee grounds, leading to a higher final beverage mass. The inverse relationship between TDS and yield thus explains the stability of the EY values, even when both parameters vary simultaneously.

From the perspective of brew strength categories, the results exhibit a consistent pattern in which the *strong* category shows the highest TDS values, followed by *medium* and *light*. Conversely, yield values gradually increase from *strong* to *light*. This pattern indicates that in *strong* brews, a lower water-to-coffee ratio produces a higher concentration of dissolved solids, whereas in *light* brews, the use of a larger volume of water results in a more diluted beverage with greater final volume. Nevertheless, the differences in EY values among the strength categories are not significant. The highest EY was observed in the *strong* category, averaging around 19.2%, while *medium* and *light* brews ranged between 18.5% and 18.8%. These findings confirm that the brewing method employed demonstrates good consistency in maintaining extraction efficiency regardless of the applied brew strength variation.

3.1.2 General Trend Observation

Across all tested density levels, Total Dissolved Solids (TDS) exhibited a gradual decline as bean density increased, while Extraction Yield (EY) remained stable within the ideal range of 18–20 %. This indicates that denser beans produced lower brew concentrations without reducing extraction efficiency, confirming that proper calibration of grind size, temperature, and brew ratio effectively compensates for density variations. The inverse relationship between bean density and TDS is shown in Figure 3.1, and the corresponding EY distribution is presented in Figure 3.2, demonstrating that although concentration decreases with density, extraction performance remains consistently optimal.

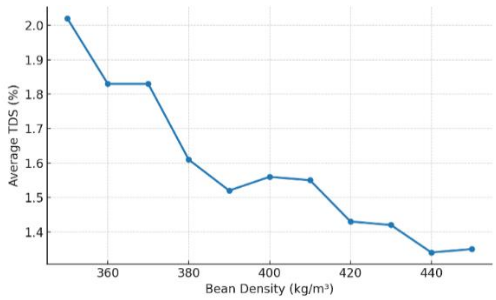

Fig. 3.1. Average Total Dissolved Solids (TDS) versus Bean Density.

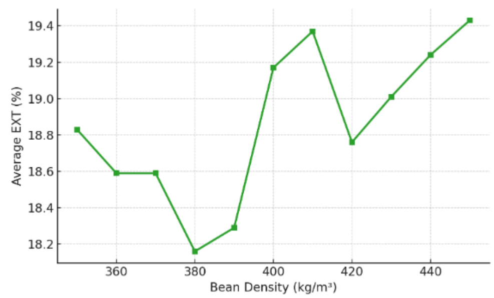

Fig. 3.2. Average Extraction Yield (EY) versus Bean Density.

The trends illustrated in Figures 3.1 and 3.2 further validate the inverse relationship between Total Dissolved Solids (TDS) and bean density, while Extraction Yield (EY) remains relatively consistent across all tested densities. The declining TDS curve indicates that as bean density increases, the compact structure of the coffee bed limits water permeability, thereby reducing the dissolution rate of soluble compounds. In contrast, the EY curve exhibits only minor variations and consistently falls within the ideal extraction range, demonstrating that the overall efficiency of the brewing process is maintained regardless of changes in concentration.

The consistent EY values across different density levels underscore the resilience of the pour-over brewing method when critical parameters such as grind particle size, brewing temperature, and pouring pattern are properly adjusted. These findings suggest that although higher-density beans yield brews with lower concentration and milder sensory intensity, they do not adversely affect extraction efficiency. Consequently, tailoring brewing parameters to accommodate variations in bean density can support both baristas and researchers in achieving stable extraction outcomes and balanced flavor characteristics.

3.1.3 Summary of Findings

1. TDS decreases progressively with increasing bean density due to lower permeability in denser coffee structures.
2. EY remains within 18–20 %, demonstrating stable and efficient brewing performance.
3. The highest EY (19.73 %) occurs at 450 kg/m^3 (strong category), achieving optimal balance between strength and efficiency.
4. The Fuzzy–TOPSIS model maintains consistency across densities by adapting brewing parameters to bean characteristics.

3.1.4 Web-Based System Implementation

To validate the applicability of the proposed decision-support framework, a web-based platform was developed using the Django (Python) environment. The system, titled Houdvan Coffee Lab – Brewing Optimization System, enables users to determine optimal brewing parameters interactively through a simple browser interface.

As shown in Figure 3.3, the interface contains two primary input fields for bean density (350–450 kg/m^3) and brew-strength category (strong, medium, or light). After entering these values and selecting the Process option, the system executes the integrated Fuzzy Tahani–TOPSIS computation to evaluate all density-related parameter combinations and identify the configuration with the highest similarity to the ideal solution.

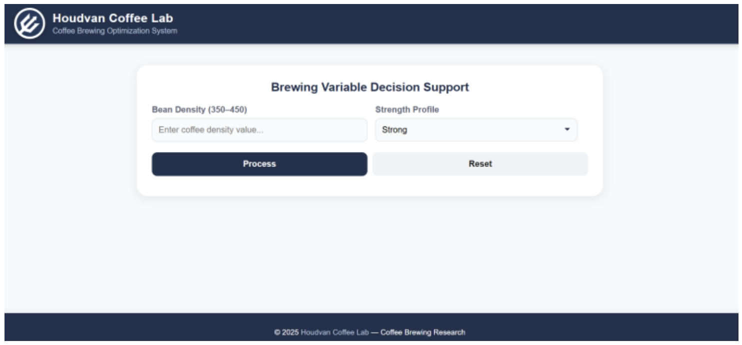

Fig. 3.3. Initial interface of the Houdvan Coffee Lab web-based decision-support system.

Following data submission, the platform generates an output comprising the recommended brewing parameters grind size, water temperature, and brew ratio—which are automatically adjusted according to the user's inputs. An example of the resulting output for a bean density of 422 kg/m^3 under the strong category is presented in Figure 3.4. The system interface displays these optimized variables together with their corresponding compatibility scores, providing users with objective, data-driven recommendations for consistent brewing performance.

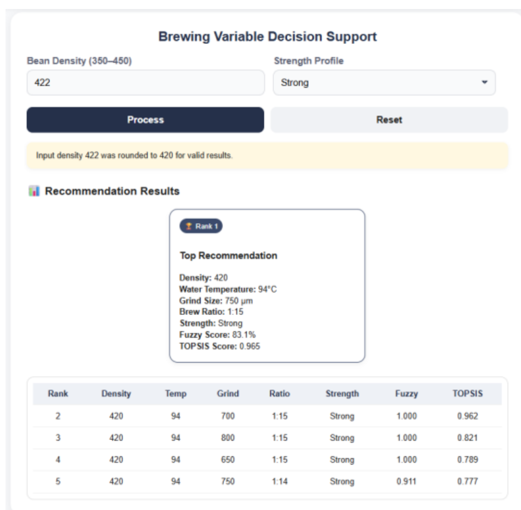

Fig. 3.4. Example output of the system for bean density = 422 kg/m^3 and strong profile.

This implementation confirms that the Fuzzy Tahani–TOPSIS hybrid model can be effectively deployed in a web environment to deliver real-time, interactive decision support. Although the example shown corresponds to the strong profile, identical computation applies to the medium and light categories, producing proportionally adjusted recommendations. The prototype demonstrates the system's capacity to integrate computational modeling with user accessibility, laying the groundwork for future adaptive brewing optimization platforms.

3.2 Discussion

3.2.1 Relation to the Fuzzy–TOPSIS Model

Experimental outcomes closely matched the Fuzzy–TOPSIS predictions introduced in Chapter 2. The recommended parameter sets generated through the combined Fuzzy Tahani inference and TOPSIS ranking using f_1–f_4 produced a controlled decline in TDS as bean density increased, while EY stayed within 18–20 %. This agreement confirms that the hybrid reasoning framework, merging linguistic rules and quantitative evaluation, performs effectively under practical brewing conditions.

For future refinement, the Fuzzy–TOPSIS framework can be further enhanced by incorporating a wider range of sensory and physicochemical parameters to improve its predictive reliability. Variables such as grind consistency, flow resistance, aroma intensity, and perceived flavor balance could be introduced to establish a stronger linkage between quantitative extraction metrics and sensory quality evaluation. Furthermore, model validation using larger datasets and comparative testing across various brewing techniques such as immersion and pressure-based systems would help enhance its generalizability and robustness. The integration of real-time sensor data, combined with adaptive fuzzy rule adjustment, may also enable dynamic optimization throughout the brewing process, resulting in a more holistic and responsive predictive model that aligns analytical performance with sensory perception in evaluating coffee quality.

4. Conclusions

This study investigated the effect of bean density on coffee brew strength and extraction performance using a hybrid Fuzzy Tahani–TOPSIS decision-support model implemented within a Django-based web application. The combined experimental and computational results indicate that as bean density increases, Total Dissolved Solids (TDS) exhibit a gradual decline, reflecting a controlled decrease in brew strength, while Extraction Yield (EY) remains consistently within the optimal range of 18–20%. These findings suggest that although bean density influences the concentration of soluble compounds, it does not compromise overall extraction efficiency when brewing parameters such as grind size, temperature, and ratio are properly calibrated.

The stable EY values observed across all density levels validate the effectiveness of the parameter configurations produced by the Fuzzy–TOPSIS framework. The model demonstrates an ability to maintain consistency through adaptive adjustment of brewing parameters, successfully translating linguistic reasoning into quantifiable and reliable recommendations. This outcome confirms the alignment between the experimental evidence, the theoretical framework established in Chapter 2, and the research objectives outlined in Chapter 1, reinforcing the robustness of the hybrid decision-support approach for coffee-brewing optimization.

For future work, expanding the model to include additional influencing factors—such as roast level, brewing method, and contact time—could provide deeper insights into the interaction between physical bean properties and extraction dynamics. Incorporating sensory and chemical evaluation would further strengthen the link between quantitative extraction metrics and perceived flavor attributes. Moreover, integrating real-time feedback and adaptive learning mechanisms into the web platform would enhance system responsiveness, enabling continuous improvement and personalized optimization in practical brewing applications. Overall, the combination of empirical experimentation and intelligent modeling establishes a data-driven foundation for achieving precision and reproducibility in coffee brewing.

5. References

Afrianto, W. F., Tanjungsari, R. J., Wati, I., Hidayatullah, T., Puspita, H., Izzudin, M., & Ilham, M. (2024). *Sustainability index analysis of traditional organic coffee agroforestry in Pati Regency , Central Java , Indonesia*. *September*. https://doi.org/10.32859/era.27.38.1-22

Aminoroaya, A., Hadi-Vencheh, A., Jamshidi, A., & Karbassi Yazdi, A. (2025). Fuzzy TOPSIS Reinvented: Retaining Linguistic Information Through Interval-Valued Analysis. *Mathematics*, *13*(17). https://doi.org/10.3390/math13172819

Angeloni, G., Masella, P., Spadi, A., Guerrini, L., Corti, F., Bellumori, M., Calamai, L., Innocenti, M., & Parenti, A. (2023). Using ground coffee particle size and distribution to remodel beverage properties. *European Food Research and Technology*, *249*(5), 1247–1256. https://doi.org/10.1007/s00217-023-04210-3

Barry Nuqoba, Kartono, Adli, F. H. S., Effendy, F., & Taufik. (2025). Enhancing Contractor Evaluation Using Fuzzy TOPSIS-Based Decision Support System. *Bit-Tech*, *8*(1), 233–242. https://doi.org/10.32877/bt.v8i1.2510

Bhumula, K. babu, & G. N, K. (2024). Using CRITIC-TOPSIS and python to examine the effect of 1-Hepatnol on the performance and emission characteristics of CRDI CI engine with split injection. *Heliyon*, *10*(11). https://doi.org/10.1016/j.heliyon.2024.e31484

Bilalovic, O., Avdagic, Z., Omanovic, S., Besic, I., Letic, V., & Tatout, C. (2020). Mathematical modelling of ground truth image for 3D microscopic objects using cascade of convolutional neural networks optimized with parameters' combinations generators. *Symmetry*, *12*(3). https://doi.org/10.3390/sym12030416

Chang, Y.-C., Chang, K.-H., & Huang, Y.-H. (2020). A novel fuzzy credit risk assessment decision support system based on the python web framework. *Journal of Industrial and Production Engineering*, *37*(5), 229–244. https://doi.org/10.1080/21681015.2020.1772385

Chaube, S., Pant, S., Kumar, A., Uniyal, S., Singh, M. K., Kotecha, K., & Kumar, A. (2024). An Overview of Multi-Criteria Decision Analysis and the Applications of AHP and TOPSIS Methods. *International Journal of Mathematical, Engineering and Management Sciences*, *9*(3), 581–615. https://doi.org/10.33889/IJMEMS.2024.9.3.030

Dong, W., Kitamura, Y., Kokawa, M., Suzuki, T., & Amini, R. K. (2024). Microstructural Modification and Sorption Capacity of Green Coffee Beans. *Foods*, *13*(21). https://doi.org/10.3390/foods13213398

Gabriel, P. Y., & Lubis, M. M. (2025). *Sustainability Analysis of Coffee Agribusiness in Indonesia : Environmental , Economic , and Social Perspectives*. *7*(2), 788–795. https://doi.org/10.56338/ijhess.v7i2.7284

Guinard, J. X., Frost, S., Batali, M., Cotter, A., Lim, L. X., & Ristenpart, W. D. (2023a). A new Coffee Brewing Control Chart relating sensory properties and consumer liking to brew strength, extraction yield, and brew ratio. *Journal of Food Science*, *88*(5), 2168–2177. https://doi.org/10.1111/1750-3841.16531

Guinard, J. X., Frost, S., Batali, M., Cotter, A., Lim, L. X., & Ristenpart, W. D. (2023b). A new Coffee Brewing Control Chart relating sensory properties and consumer liking to brew strength, extraction yield, and brew ratio. *Journal of Food Science*, *88*(5), 2168–2177. https://doi.org/10.1111/1750-3841.16531

Lee, W. T., Smith, A., & Arshad, A. (2023). Uneven extraction in coffee brewing. *Physics of Fluids*, *35*(5), 054110. https://doi.org/10.1063/5.0138998

Liu, H., Liu, D., Wang, W., Zhang, X., Tuly, J., Li, H., & Ma, H. (2024). Dual-frequency countercurrent ultrasonic-assisted extraction of the cold brew coffee and in situ real-time monitoring of extraction process. *Ultrasonics Sonochemistry*, *111*. https://doi.org/10.1016/j.ultsonch.2024.107118

Mahmoudian Azar Sharabiani, A., & Mousavi, S. M. (2023). A Web-Based Decision Support System for Project Evaluation with Sustainable Development Considerations Based on Two Developed Pythagorean Fuzzy Decision Methods. *Sustainability (Switzerland)*, *15*(23). https://doi.org/10.3390/su152316477

Mallu, S., & Saharuddin. (2023). COMPARATIVE ANALYSIS OF DECISION SUPPORT SYSTEMS USING THE FUZZY TAHANI AND WASPAS METHODS IN SELECTING TOURISM PLACES TO VISIT IN MAKASSAR. *Nusantara Hasana Journal*, *2*(9), 269–283.

Meng, F., Li, Z., Dong, Q., Fu, L., & Zhang, Y. (2023). Profit allocation on a four-echelon supply chain in perspective of cooperative games on augmenting systems. *Expert Systems with Applications*, *219*, 119639. https://doi.org/https://doi.org/10.1016/j.eswa.2023.119639

Nguyen, N. B. T., Lin, G. H., & Dang, T. T. (2021). A two phase integrated fuzzy decision-making framework for green supplier selection in the coffee bean supply chain. *Mathematics*, *9*(16). https://doi.org/10.3390/math9161923

Licata, P. (2019). *How To Get The Best From Your Coffee Book: Vol. Vol. 1* (E-Book). Pete Licata Consulting, LLC.

SCA. (2022). *SCA Coffee Equipment Series SCA Standard 310-2021 Home Coffee Brewers: Specifications and Test Methods*.

Schmieder, B. K. L., Pannusch, V. B., Vannieuwenhuyse, L., Briesen, H., & Minceva, M. (2023). Influence of Flow Rate, Particle Size, and Temperature on Espresso Extraction Kinetics. *Foods*, *12*(15). https://doi.org/10.3390/foods12152871

Várady, M., Tauchen, J., Klouček, P., & Popelka, P. (2022). Effects of Total Dissolved Solids, Extraction Yield, Grinding, and Method of Preparation on Antioxidant Activity in Fermented Specialty Coffee. *Fermentation*, *8*(8). https://doi.org/10.3390/fermentation8080375

Wahdiniwaty, R., Syafei, M. Y., Haryadi, Y., & Nurdiansyah, D. (2025). EMPOWERING COFFEE FARMERS IN SUKASARI , MOUNT MANGLAYANG , THROUGH NATIONAL STANDARDS OF INDONESIA (SNI) FOR POST-HARVEST QUALITY IMPROVEMENT TO ACCESS INTERNATIONAL MARKETS. *Indonesian Journal of Studies on Humanities, Social Sciences, and Education (IJHSED)*, *2*(2), 64–75.

Xu, S., Liu, Y., Sun, Z., Chen, G., Ma, F., Yang, N., de Melo Virginio Filho, E., & Fisk, I. D. (2023). Effects of agro-forestry systems on the physical and chemical characteristics of green coffee beans. *Frontiers in Nutrition*, *10*. https://doi.org/10.3389/fnut.2023.1198802