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Impact of different process parameters on the quality of raw milk: an optimization-based approach

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Abstract: The quality of raw milk is of paramount importance, as it directly affects the safety and nutritive value of dairy products. This research paper delves into the significant influence of various process parameters on the quality attributes of raw milk using an optimization-based approach. Through a comprehensive experimental design, this study systematically investigates the effects of parameters such as pH, temperature, and density. Utilizing a response surface methodology (RSM) coupled with statistical analysis, the paper evaluates the interplay between these process parameters and the resulting quality outcomes. By employing Box Behnken Design (BBD) experiments, the research establishes mathematical models that predict the impact of different parameter combinations on raw milk quality. These models provide valuable insights into the optimal conditions for achieving desired quality attributes while ensuring safety and stability. The findings underscore the intricate relationships between process parameters and raw milk quality, revealing opportunities for enhancing milk processing practices. Furthermore, the study highlights the potential for optimizing raw milk quality within practical constraints, guiding dairy industry professionals in making informed decisions to balance quality and efficiency. Ultimately, this research contributes to a deeper understanding of the complex dynamics governing raw milk quality and offers a framework for optimizing dairy processing methods to meet both consumer expectations and regulatory standards.

Keywords: Raw milk; Optimization; Box-Behnken Design; ANOVA; Quality control.

1. Introduction:

Raw milk serves as a vital raw material for the dairy industry, forming the foundation for a diverse range of dairy products consumed globally. The quality of raw milk is a critical determinant of the safety, nutritional value, and organoleptic characteristics of dairy products. As consumer demands for high-quality and safe food products continue to rise, it becomes imperative to understand the multifaceted relationship between process parameters and the quality attributes of raw milk [1].

The quality of raw milk is a complex outcome influenced by various intrinsic and extrinsic factors. Intrinsic factors encompass the inherent composition of milk, including fat content, protein composition, and microbial load, while extrinsic factors relate to the processing conditions applied during milk collection, storage, and transportation [2]. Achieving consistent and desirable quality attributes in raw milk requires a comprehensive understanding of how these intrinsic and extrinsic factors interact and how they can be controlled and optimized [3]. Additionally, the microbial load of milk is also an important component and even a minute change in the composition may cause a spectrum of diseases [4, 5, 6].

Over the years, advancements in technology and scientific understanding have facilitated the optimization of dairy processing operations, leading to improved quality and safety of dairy products. An emerging approach in this domain is optimization-based research, which aims to identify the optimal combination of process parameters that result in the desired quality outcomes. This approach not only enhances the efficiency of dairy operations but also contributes to the reduction of resource wastage and environmental impact [7, 8, 9].

The present research focuses on investigating the impact of different process parameters on the quality of raw milk through an optimization-based approach. By systematically exploring the effects of storage temperature, pH, and density on the raw milk quality. Through the application of response surface methodology (RSM) and statistical analysis, the research aims to establish predictive models that elucidate the influence of various parameter combinations on raw milk quality.

The outcomes of this research hold substantial significance for the dairy industry, as they provide valuable insights into the optimization of processing parameters to achieve consistent and desirable raw milk quality attributes. By bridging the gap between theoretical understanding and practical application, this study contributes to the enhancement of dairy processing practices, aligning them with the evolving demands of consumers and regulatory standards [10, 11, 12]. As such, the investigation into the impact of process parameters on raw milk quality stands to advance the field of dairy science and foster innovations in the production of high-quality dairy products. Overall, this work would be helpful towards creating a better and sustainable future [13, 14, 15].

2. Materials and Methods:

The determination of the milk quality depends upon several parameters. The literature reported that for conducting optimization, at least three different process parameters are required [7]. Accordingly, after an exhaustive literature search, three different process parameters were shortlisted namely the pH, storage temperature, and the density of the milk [16, 17]. The lower and upper limits of each respective level were also defined through an elaborate literature search. The details of the three factors and their respective levels have been detailed in Table 1.

Table 1 Different factors and their levels adopted in this study.

Factors	Lower Limit	Upper Limit
A: pH	6.4	6.9
B: Temperature	4	32
C: Density	1.025	1.035

As the response outcome of this study, a grading system was adopted. grading scale was developed with 1 being the best and 3 being the worst. The rule for the selection was adopted such that if all three of the parameters were satisfactory the quality was graded as 1, if only 2 of the parameters were satisfactory it was graded a 2 and if only 1 or lesser than 1 of the parameters were satisfactory it was graded a 3. The response surface methodology was adopted for this study. Among various RSM-based approaches, the BBD is the most frequently used approach due to process simplicity, and precision. The Box-Behnken design is a statistical experimental design technique that plays a pivotal role in optimizing processes and understanding the relationships between multiple variables. Named after its developers George E.P. Box and Donald W. Behnken, this design method offers a balanced and efficient approach to exploring the effects of several factors on a response variable. It is particularly valuable when conducting experiments that involve multiple factors with both continuous and categorical levels. One of the major advantages of the Box-Behnken design is its efficiency in reducing the number of experimental runs required compared to a full factorial design. This efficiency is especially crucial in cases where experimentation can be time-consuming or costly. The design is also designed to be rotatable, meaning that its efficiency remains consistent even when certain factors have stronger effects than others [7]. Researchers can utilize the results obtained from the Box-Behnken design to create response surface models, which provide insights into how the factors interact to influence the response variable. These models enable the identification of optimal parameter settings that lead to desired outcomes, facilitating process optimization and quality improvement. The design's versatility and flexibility have made it a widely adopted technique across various fields. The entire optimization study was carried out by using the software named Design Expert® version 13.05. The experimental design was obtained from the software and has been presented in Table 2 along with the response variables [8].

Table 2: Design of experiment obtained from the software.

STD	RUN	FACTOR 1: pH UNIT	FACTOR 2: TEMPRATURE CELCIUS	FACTOR 3: DENSITY GM/CM3	RESPONSE ONE MILK QUALITY IN UNITS
4	1	6.9	32	1.03	2
13	2	6.65	18	1.03	2
10	3	6.65	32	1.025	2
5	4	6.4	18	1.025	1
1	5	6.4	4	1.03	2
12	6	6.65	32	1.035	2
9	7	6.65	4	1.025	3
11	8	6.65	4	1.035	2
2	9	6.9	4	1.03	2
15	10	6.65	18	1.03	2
8	11	6.9	18	1.035	3
14	12	6.65	18	1.03	1
3	13	6.4	32	1.03	2
6	14	6.9	18	1.035	2
7	15	6.4	18	1.025	1

3. Results and Discussion:

The data presented in Table 2 was fed to the Design Expert software for further optimization procedures. The ANOVA results were obtained from the software and have been presented in Table 3 in order to determine the statistically significant model terms. ANOVA helps determine whether the variation in the response variable can be attributed to the variations in the factors being studied or if the observed differences could have occurred by random chance. This statistical significance provides confidence that the identified relationships between factors and the response variable are not merely due to noise in the data. ANOVA results also provide insights into the individual and interactive effects of the factors on the response variable. By evaluating the significance of each factor and their interactions, researchers can identify which factors have the most substantial impact on the response. This information guides decision-making by highlighting which factors need to be prioritized for optimization. Furthermore, the ANOVA results help to assess the adequacy of the regression model developed using the experimental data. If the ANOVA results indicate that the model is a good fit for the data, it suggests that the model can be trusted for making predictions within the range of the factors studied. Conversely, if the ANOVA results suggest a lack of fit, it may indicate that the model needs refinement or further exploration of factors. ANOVA results aid in identifying the optimal factor settings that lead to desirable responses. By analyzing the factor levels associated with the most favorable outcomes, researchers can determine the conditions that maximize or minimize the response variable, facilitating the optimization process. ANOVA also evaluates the significance of interactions between factors. Interactions can sometimes have non-additive effects on the response variable, meaning that the combined effect of two factors is not simply the sum of their individual effects. Recognizing and understanding significant interactions is crucial for accurately predicting responses across a wide range of factor combinations. Thus, the significance of ANOVA results contributes to a deeper understanding of the underlying process. Researchers gain insights into how different factors influence the response variable and how they interact with one another. This understanding can lead to improved process control, better problem-solving, and informed decision-making [7, 8, 18].

Table 3: ANOVA result obtained from the software.

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	0.7809	6	0.1302	2.38	0.1281	not significant

A-pH	0.1642	1	0.1642	3.00	0.1217	
B-Temperature	0.0000	1	0.0000	0.0000	1.0000	
C-Density	0.1642	1	0.1642	3.00	0.1217	
AB	0.2756	1	0.2756	5.03	0.0552	
AC	0.1340	1	0.1340	2.44	0.1565	
BC	0.0429	1	0.0429	0.7827	0.4021	
Residual	0.4384	8	0.0548			
Lack of Fit	0.3710	6	0.0618	1.84	0.3937	not significant
Pure Error	0.0673	2	0.0337			
Cor Total	1.22	14				

After conducting the ANOVA, the final model equation was obtained containing all the statistically significant terms which have been presented below (Equation 1);

Sq. Rt. (Quality Index) = 1.36 + 0.1433pH + 0.0001×Temperature – 0.1433×Density + 0.2625×pH×Temperature – 0.1830×pH×Density + 0.1036×Temperature×Density. ………(i).

By charting the empirically discovered and model-predicted values under the provided factor space, a normality plot was created to demonstrate the correctness and precision of the suggested model equation (indicated in Figure 1). The model-predicted reaction was discovered to be pretty close to the experimentally obtained response, as was observed. As a result, it can be said that the constructed model has good precision and accuracy [8].

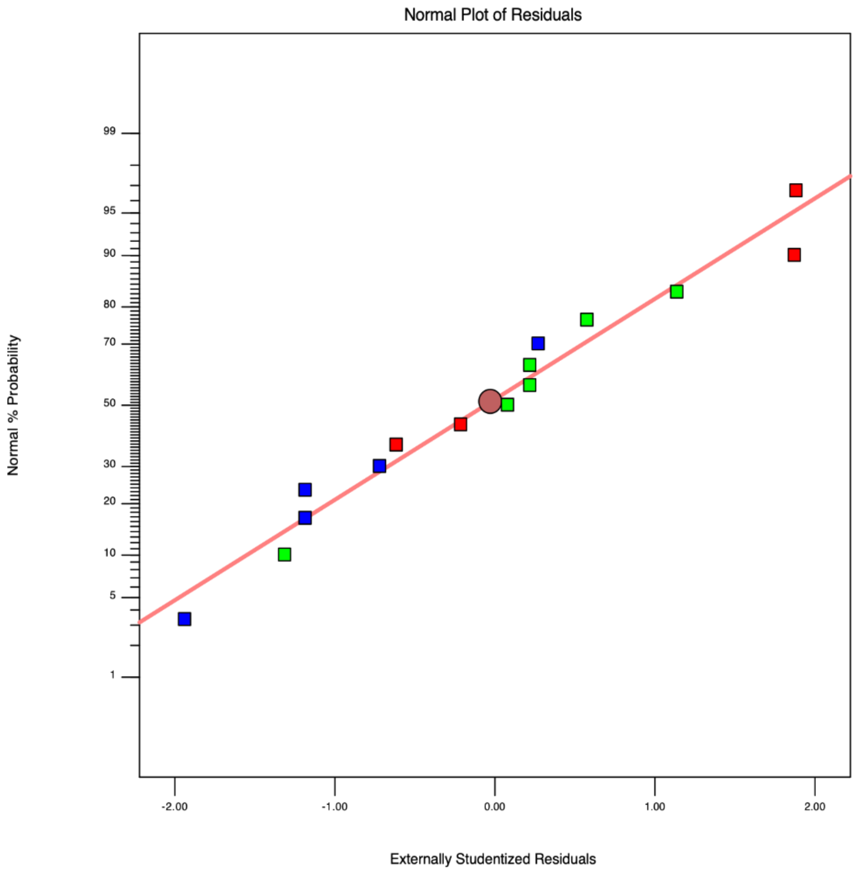

Figure 1: Plot showing the experimentally determined and projected reaction by the model.

Thereafter the impact of the different factors (using two factors at a time) on the process output was then examined using the three-dimensional response surface curves. Figure 2 shows the results that were attained [7].

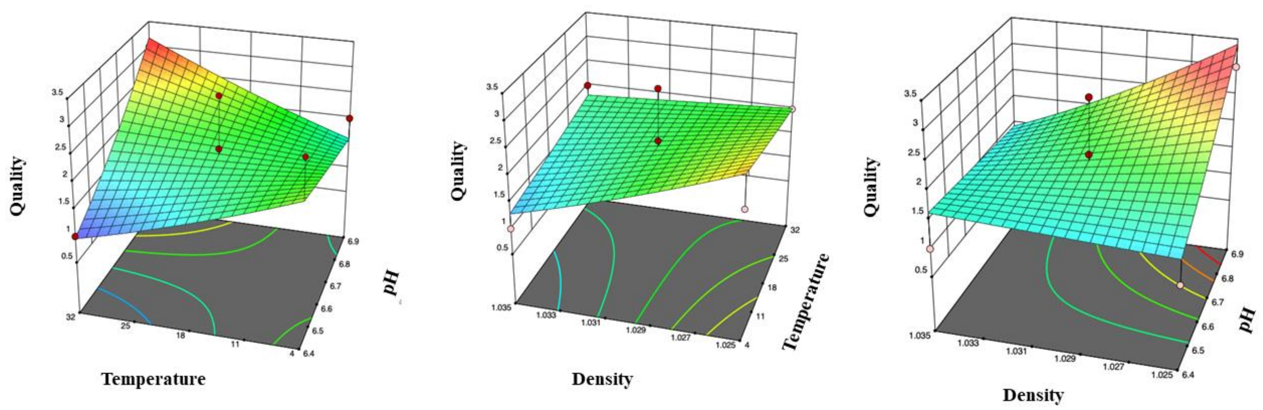

Figure 2. Response Surface 3-Dimensional interaction plots among different factors (two at a time) to define their cumulative impact on the response variable (Milk Quality). (A): Synergistic impact of Temperature and pH towards the Milk Quality; (B) Synergistic impact of Density and Temperature towards the Milk Quality; (C) Synergistic impact of Density and pH towards the Milk Quality.

Figure 2A indicates the synergistic impact of temperature and pH on the response outcome. At the respective lower levels of both the factors high response outcome was recorded. With the increase in levels of both the factors initially a drop in the response variable was recorded and threrafter a steep rise of the response variable was observed. Figure 2B and 2C indicates that the synergistic impacts of density & temperature (2B) and density & pH (2C) were almost similar where at the respective lower levels, the response outcome was lower. However, with the increment of the levels, the response outcome improved. The increment was more profound in case of Figure 2C. The obtained results were found to be in sync with the previously reported studies. With the increase in the density, and the lowering of the pH and the preservation temperature, the quality of milk is expected to increase. Accordingly, the factor effect study holds good significance which in turn indicates the goodness of fit of the proposed model.

Finally, an attempt was made to locate the factor setting level corresponding to the best response outcome. This was done on the basis of D-optimality (or desirability) index. Typically, the Desirability varies between 0-1, where 0 is the worst and 1 is the selection parameter [7, 8]. The software provided 100 such solutions, from where the best 5 has been presented in Table 4. The optimum condition was indicated and highlighted in Table 4.

Table 4: Selection of the optimum setting level based on Desirability index.

Number	pH	Temperature	Density	Quality index	Desirability	Status
1	6.566	16.632	1.030	2.985	1.000	Selected
2	6.900	18.000	1.025	2.965	1.000	Rejected
3	6.650	18.000	1.030	2.947	1.000	Rejected
4	6.900	32.000	1.030	2.932	1.000	Rejected
5	6.900	18.000	1.035	2.842	1.000	Rejected

4. Conclusion and Future Recommendations:

In the pursuit of enhancing the quality of raw milk for optimal dairy product outcomes, this experimental study employed an optimization-based approach to investigate the intricate relationships between process parameters and raw milk quality attributes. Through a systematic exploration of storage temperature, pH, and density coupled with the utilization of Box-Behnken design and response surface methodology, this research has unveiled valuable insights that contribute to both theoretical understanding and practical applications in the dairy industry. The results obtained from the experimentation and subsequent analysis have shed light on the multifaceted influences of process parameters on the key quality indicators of raw milk. The identification of statistically significant main effects and interactions has provided a comprehensive understanding. These insights are pivotal for designing more effective and efficient milk processing strategies that ensure both product quality and safety. Furthermore, the establishment of predictive models based on the experimental data has empowered the prediction of raw milk quality responses across a range of parameter combinations [19, 20]. These models facilitate the identification of optimal conditions that maximize desirable attributes and minimize undesirable variations. The implications of this research extend beyond the laboratory, directly impacting the dairy industry's ability to consistently deliver high-quality products that meet consumer expectations and regulatory standards [21]. The findings highlight the importance of process optimization as a means to balance quality enhancement and resource utilization. By merging scientific understanding with practical application, this study bridges the gap between theory and industry practice, guiding professionals in making informed choices that have far-reaching implications for product quality and market competitiveness [22].

As we move forward, this research lays the foundation for further investigations into more complex factors and their interactions, as well as exploring the applicability of optimization-based approaches in other areas of food processing. The holistic perspective gained from this study underscores the dynamic nature of raw milk quality and reaffirms the significance of continual research and innovation to maintain and elevate the standards of dairy products in a rapidly evolving global market.

In summation, the optimization-based approach presented in this experimental paper offers a valuable framework for refining raw milk processing methods and enhancing the quality of dairy products. The study's findings illuminate a pathway for the dairy industry to embrace optimization strategies that elevate product quality, foster efficiency, and support the evolving demands of consumers and regulations.

Conflict of Interest: No potential Conflict of Interest was reported in the reported study.

References:

1. Pal, M., Mulu, S., Tekle, M., Pintoo, S. V., & Prajapati, J. (2016). Bacterial contamination of dairy products. Beverage and food world, 43(9), 40-43.
2. Guo, X., Yu, Z., Zhao, F., Sun, Z., Kwok, L. Y., & Li, S. (2021). Both sampling seasonality and geographic origin contribute significantly to variations in raw milk microbiota, but sampling seasonality is the more determining factor. Journal of Dairy Science, 104(10), 10609-10627.
3. Roy, R., Shil, S., Choudhary, D. K., Mondal, P., Adhikary, P., Manna, U., ... & Maji, M. (2022). Conversion of glucose into calcium gluconate and determining the process feasibility for further scaling-up: An optimization approach. Int. J. Exp. Res. Rev, 27, 1-10.
4. Ghosal, A., Roy, R., Sharma, K., Mitra, P., & Vora, K. (2022). Antibiofilm activity of Phytocompounds against of *Staphylococcus aureus* Biofilm forming Protein-In silico study. American Journal of Applied Bio-Technology Research, 3(1), 27-29.
5. Banik, S., Nath, P. C., & Roy, R. (2023). Microbiome and gut-brain axis affecting stress behavior. American Journal of Applied Bio-Technology Research, 3(4), 17-34.
6. Parveen, S., Sur, T., Sarkar, S., & Roy, R. (2023). Antagonist Impact of Selenium-Based Nanoparticles Against Mycobacterium tuberculosis. Applied Biochemistry and Biotechnology, 1-9.
7. Roy, R., & Ray, S. (2020). Development of a non-linear model for prediction of higher heating value from the proximate composition of lignocellulosic biomass. Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, 1-14.
8. Roy, R., & Ray, S. (2022). Upgradation of an Agro-residue by Acid Pretreatment into a Solid Fuel with Improved Energy Recovery Potential: An Optimization Study. Arabian Journal for Science and Engineering, 47(5), 6311-6323.
9. Dey, P., Roy, R., Mukherjee, A., Krishna, P. S., Koijam, R., & Ray, S. (2022). Valorization of Waste Biomass as a Strategy to Alleviate Ecological Deficit: A Case Study on Waste Biomass Derived Stable Carbon. Advanced Microscopy, 167-196.
10. Su, Q., Dong, J., Zhang, D., Yang, L., & Roy, R. (2022). Protective effects of the bilobalide on retinal oxidative

stress and inflammation in streptozotocin-induced diabetic rats. Applied Biochemistry and Biotechnology, 194(12), 6407-6422.

11. Song, B., Liu, X., Dong, H., & Roy, R. (2023). miR-140-3P Induces Chemotherapy Resistance in Esophageal Carcinoma by Targeting the NFYA-MDR1 Axis. Applied Biochemistry and Biotechnology, 195(2), 973-991.
12. Qiu, S., Wu, X., Wu, Q., Jin, X., Li, H., & Roy, R. (2023). Pharmacological Action of Baicalin on Gestational Diabetes Mellitus in Pregnant Animals Induced by Streptozotocin via AGE-RAGE Signaling Pathway. Applied Biochemistry and Biotechnology, 1-16.
13. Roy, R., & Ray, S. (2019). Effect of various pretreatments on energy recovery from waste biomass. Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, 1-13.
14. Roy, R., Debnath, D., & Ray, S. (2022). Comprehensive assessment of various lignocellulosic biomasses for energy recovery in a hybrid energy system. Arabian Journal for Science and Engineering, 47(5), 5935-5948.
15. Vipparla, C., Sarkar, S., Manasa, B., Pattela, T., Nagari, D. C., Aradhyula, T. V., & Roy, R. (2022). Enzyme Technology in Biofuel Production. In Bio-Clean Energy Technologies Volume 2 (pp. 239-257). Singapore: Springer Nature Singapore.
16. Pandey, A., Srivastava, S., & Kumar, S. (2019). Isolation, screening and comprehensive characterization of candidate microalgae for biofuel feedstock production and dairy effluent treatment: a sustainable approach. Bioresource technology, 293, 121998.
17. Barbosa, M. S., dos Santos Alves, R. P., de Souza Rezende, I., Pereira, S. S., Campos, G. B., Freitas, L. M., ... & Timenetsky, J. (2020). Novel antigenic proteins of Mycoplasma agalactiae as potential vaccine and serodiagnostic candidates. Veterinary Microbiology, 251, 108866.
18. Noordin, M. Y., Venkatesh, V. C., Sharif, S., Elting, S., & Abdullah, A. (2004). Application of response surface methodology in describing the performance of coated carbide tools when turning AISI 1045 steel. Journal of materials processing technology, 145(1), 46-58.
19. Roy, R., Srinivasan, A., Bardhan, S., & Paul, T. (2022). Evaluation of the Expression of CD-4 and CD-45 Count among Patients Having Non-Small Cell Lung Cancer. Journal homepage: www. ijrpr. com ISSN, 2582, 7421.
20. Li, R., & Roy, R. (2023). Gut Microbiota and Its Role in Anti-aging

Phenomenon: Evidence-Based Review. Applied Biochemistry and Biotechnology, 1-15.

21. Roy, R., Chakraborty, A., Jana, K., Sarkar, B., Biswas, P., & Madhu, N. R. (2023). The Broader Aspects of Treating Diabetes with the Application of Nanobiotechnology. In Advances in Diabetes Research and Management (pp. 137-162). Singapore: Springer Nature Singapore.
22. Roy, R., Sarkar, S., Kotak, R., Nandi, D., Shil, S., Singha, S., ... & Tarafdar, S. (2022). Evaluation of the Water Quality Parameters from Different Point Sources: A Case Study of West Bengal. American Journal of Applied Bio-Technology Research, 3(3), 18-28.