Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control
Journal homepage: http://kinetik.umm.ac.id
ISSN: 2503-2267
Vol. 11, No. 2, May, Pp. 227-236

Modeling and simulation of a heat and airflow control system in a fish smoking chamber using K-NN

Muhammad Edy Hidayat*[1], Alang Sunding[2], Umar Muhammad[3], Irvawansyah[3]
Program Studi Diploma III Teknik Mekatronika, Politeknik Bosowa, Indonesia[1]
Program Studi Diploma III Perawatan dan Perbaikan Mesin, Politeknik Bosowa, Indonesia[2]
Program Studi Diploma III Teknik Listrik, Politeknik Bosowa, Indonesia[3]

Article Info

Keywords:
Fish Smoking Chamber, Heat and Airflow Control, K-Nearest Neighbor Algorithm, Modeling and Simulation

Article history:
Received: September 16, 2025
Accepted: January 13, 2026
Published: May 01, 2026

Cite:
Muhammad Edy Hidayat, A. Sunding, U. Muhammad, and Irvawansyah, "Modeling and Simulation of a Heat and Airflow Control System in a Fish Smoking Chamber Using K-NN", *KINETIK*, vol. 11, no. 2, May. 2026. https://doi.org/10.22219/kinetik.v11i2.2492

*Corresponding author.
Muhammad Edy Hidayat
E-mail address:
edyhidayat@politeknikbosowa.ac.id

Abstract

This study presents the modeling and simulation of a heat and airflow control system in a fish smoking chamber using the K-Nearest Neighbors (K-NN) algorithm. Accurate control of temperature and airflow is crucial for ensuring consistent product quality, flavor, texture, and microbial safety in smoked fish. Traditional methods often face challenges in maintaining stable chamber conditions due to nonlinear interactions between heat sources, airflow distribution, and chamber geometry. The research was conducted using a structured methodology consisting of system modeling, K-NN algorithm development, simulation, and performance evaluation. The results demonstrate that the K-NN model achieved optimal performance at k = 5, with an overall prediction accuracy of 92.8%. The Root Mean Square Error (RMSE) was recorded at 1.85 °C for temperature prediction and 0.18 m/s for airflow, confirming the model's robustness. Compared with conventional approaches, K-NN outperformed Linear Regression and achieved higher accuracy with less complexity than Artificial Neural Networks (ANN). The implications of these findings indicate that predictive modeling enables better process stability, reduces the risk of uneven smoking, and lowers energy consumption. The novelty of this research lies in the dual prediction of heat and airflow, providing a comprehensive framework for smart control in traditional food processing. While the study is limited to simulations, it offers valuable insights for future experimental implementation and integration into intelligent smoking chamber systems.

1. Introduction

Fish smoking is one of the most important preservation techniques used in many developing countries, especially in coastal regions where fish constitutes a major source of protein and livelihood [1]. The process involves exposing fish to a controlled combination of heat and smoke over a certain period to achieve dehydration, improve flavor, and extend shelf life [2]. Despite its long history and cultural relevance, traditional smoking practices are often inefficient and produce inconsistent results. One of the key challenges lies in the inability to precisely regulate heat and airflow within the smoking chamber [3]. Without adequate control, the process can result in uneven smoking, texture variation, nutrient loss, and, in some cases, microbial contamination due to incomplete drying [4].

The urgency of introducing a proper control system arises from the sensitivity of fish to both temperature and airflow distribution during smoking [5]. If the chamber temperature is too low, the drying process is prolonged, encouraging microbial growth and leading to spoilage [6]. Conversely, if the temperature is too high, the fish may burn or undergo excessive protein denaturation, negatively affecting nutritional and sensory qualities [7]. Similarly, airflow inside the chamber plays a crucial role in ensuring even smoke circulation and moisture removal. Poorly managed airflow can create hot and cold spots, resulting in non-uniform smoking, where some fish are overprocessed while others remain underprocessed [8]. These issues directly reduce product quality, market value, and consumer safety, while also increasing energy consumption [9].

Several research efforts have attempted to address these challenges. Studies have shown that conventional methods, such as manual adjustment or simple thermostats, are insufficient in providing consistent performance, particularly under variable environmental conditions [10]. Advanced approaches, such as proportional–integral–derivative (PID) controllers, have been implemented in thermal systems and food processing equipment. However, these controllers often struggle to adapt to the nonlinearities and dynamic changes present in smoking chambers, such as fluctuating ambient humidity, variable fish load, and unpredictable heat transfer dynamics [11]. Consequently, there is a growing interest in applying machine learning algorithms to food processing control systems, as they offer data-driven adaptability and predictive accuracy [12].

While conventional PID controllers have been implemented in fish smoking systems, they often struggle to adapt to dynamic uncertainties, such as fluctuations in ambient humidity and variations in fish load. The primary issue lies in their reliance on rigid linear mathematical models, whereas the dynamics within a smoking chamber are highly nonlinear and stochastic. The selection of the K-Nearest Neighbors (K-NN) algorithm is justified by its non-parametric nature, which does not assume a specific data distribution. This makes it robust for modeling complex non-linear systems, such as heat and airflow distribution, without requiring the extensive hyperparameter tuning often associated with Artificial Neural Networks (ANN). K-NN provides accurate local control predictions by leveraging historical patterns, which is highly suitable for systems with continuously shifting sensor data.

The K-Nearest Neighbors (K-NN) method, in particular, has been widely recognized for its simplicity and effectiveness in classification and prediction tasks [13]. Although traditionally used in pattern recognition and data mining, its application in thermal system modeling and control is gaining attention [14]. By leveraging the K-NN algorithm, the temperature and airflow behavior inside the smoking chamber can be predicted based on historical and simulated data patterns [15]. This predictive capability enables more accurate adjustments of control inputs, ensuring that the chamber maintains optimal conditions throughout the smoking process [16].

In this research, a modeling and simulation approach is employed to design a heat and airflow control system for a fish smoking chamber using the K-NN algorithm. Simulation provides a cost-effective and flexible platform to test and validate control strategies without the need for extensive physical prototypes, which are often expensive and time-consuming to construct. Through this study, the dynamic behavior of the smoking chamber can be better understood, and the feasibility of applying machine learning-based predictive control can be evaluated.

The novelty of this research lies in the application of K-NN for heat and airflow control in fish smoking chambers, which has not been extensively studied. Unlike conventional approaches, this method combines adaptive data-driven modeling with predictive simulation, offering several advantages: (i) improved temperature and airflow regulation, (ii) enhanced consistency and safety of smoked fish products, (iii) reduced energy consumption, and (iv) the potential to be scaled and implemented in small- and medium-scale fish processing enterprises. Therefore, this study contributes not only to the advancement of intelligent control systems in food processing but also to the sustainability of fish preservation practices in coastal communities.

2. Research Method

The research methodology is discussed in this section, organized into several subsections that describe the methods employed in the study.

2.1 Research Design

This study was conducted through a structured sequence of stages consisting of research design, modeling and simulation, algorithm development, testing procedures, and data acquisition. The overall methodology ensures the systematic development and validation of a heat and airflow control system for a fish smoking chamber using the K-Nearest Neighbors (K-NN) algorithm.

The present study adopts a modeling- and simulation-based research design to investigate the heat and airflow control system in a fish smoking chamber using the K-Nearest Neighbors (K-NN) algorithm. A simulation approach was selected because it allows comprehensive analysis of thermal and fluid dynamics behavior without requiring immediate physical prototyping, thereby reducing both cost and time [17].

The design framework consists of three main components: system modeling, algorithm integration, and performance evaluation. First, the fish smoking chamber is modeled as a controlled thermal–fluid environment in which heat transfer and airflow dynamics are the primary variables. The system inputs include heating power, fan speed, and initial environmental conditions such as chamber temperature and humidity. The system outputs consist of spatial temperature distribution and airflow velocity fields inside the chamber.

Second, the K-NN algorithm is integrated into the design to provide predictive modeling of chamber conditions. The algorithm utilizes simulation-generated datasets to estimate chamber behavior under varying operational parameters. Unlike conventional control techniques, K-NN applies a data-driven, non-parametric approach that enables adaptive prediction based on prior patterns [18]. This design choice is particularly relevant for nonlinear processes, such as fish smoking, where thermal dynamics and airflow behavior are influenced by multiple interacting variables.

Third, the design incorporates a validation and performance evaluation stage. Simulation results are compared with established heat transfer and fluid dynamics theory [19] to ensure accuracy. The predictive capability of K-NN is then assessed by analyzing error metrics such as Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), which are widely used in evaluating model performance [20]. This stage provides insights into the effectiveness of the proposed control system and highlights the potential improvements in consistency, energy efficiency, and product quality.

The overall research design, therefore, emphasizes a systematic and iterative process: (i) modeling the fish smoking chamber, (ii) generating data through simulations, (iii) applying and testing the K-NN algorithm, and (iv) evaluating prediction accuracy against theoretical and empirical benchmarks. Through this design, the study ensures a structured pathway to demonstrate the feasibility of integrating machine learning approaches into fish smoking chamber control systems.

2.2 Research Procedure

The research procedure in this study was systematically structured into several stages to ensure the reliability and reproducibility of the results. The sequence of the procedure is described as follows:

1. Problem Identification and Requirement Analysis
   The study began with the identification of the need for a reliable control system in a fish smoking chamber, specifically focusing on maintaining stable heat distribution and also the airflow. This stage involved analyzing operational challenges in traditional smoking processes, reviewing existing studies, and determining the scope of the proposed solution.
2. Modeling of the Fish Smoking Chamber
   A simplified mathematical and geometrical model of the fish smoking chamber was developed to represent heat transfer and airflow distribution phenomena. The model considered parameters such as chamber dimensions, heat sources, airflow paths, and the thermal conductivity of the chamber walls. This stage provided the foundation for subsequent simulation activities.
3. Development of the Control Algorithm
   The K-Nearest Neighbor (K-NN) algorithm was adopted as the primary control strategy due to its capability in pattern recognition and prediction. The procedure included defining the dataset structure, preprocessing data, setting the value of k, and training the model using simulated input–output relationships between temperature, airflow, and chamber conditions.
   K-NN is particularly effective for non-linear systems because it operates on the principle of feature space proximity rather than a global linear function. In a fish smoking chamber, the interaction between fan speed, heat intensity, and internal geometry creates irregular data patterns. K-NN captures these local patterns by comparing real-time inputs to their nearest neighbors in the dataset. This allows the system to maintain high precision even when the relationships between variables change dynamically, offering a more robust alternative to traditional linear modeling.
4. Simulation Setup and Execution
   The model was implemented in a simulation environment using computational tools. Simulations were conducted to evaluate how the proposed K-NN–based controller responded to variations in heat sources and airflow disturbances. The testing procedure emphasized evaluating performance under different operating scenarios to replicate real smoking conditions.
5. Testing and Validation
   The testing stage involved running multiple simulation iterations to validate the accuracy and stability of the control system. Performance indicators such as temperature stability, airflow uniformity, and response time were recorded and analyzed. The validation process also included comparisons with baseline conditions (without control) to demonstrate improvement.
6. Data Acquisition and Analysis
   All simulation results, including numerical data and graphical outputs, were collected for further analysis. Data acquisition focused on recording trends, identifying anomalies, and quantifying the effectiveness of the K-NN algorithm in maintaining desired chamber conditions. The acquired data then became the basis for the results and discussion section.

This step-by-step procedure ensured that the study followed a coherent path from problem definition to the acquisition of valid findings, aligning with standard practices in modeling and simulation research.

2.3 Testing Procedure

The testing procedure in this study was designed to evaluate the performance, stability, and accuracy of the proposed K-NN–based control system in regulating heat and airflow within the fish smoking chamber model. The procedure was carried out in a structured sequence, as outlined below:

1. Definition of Performance Criteria
   The first step was establishing the key performance indicators (KPIs) to assess system effectiveness. The selected indicators included: (i) temperature stability (the ability to maintain the chamber temperature within the optimal smoking range (60–80 °C)); (ii) airflow uniformity (the capacity of the control system to distribute airflow evenly across the chamber); and (iii) response time (the speed of the system in responding to disturbances or changes in heat source and airflow).
2. Preparation of Simulation Scenarios
   Multiple simulation scenarios were created to replicate realistic operating conditions. These scenarios involved variations in: (i) initial chamber temperature; (ii) heat source fluctuations; (iii) external airflow disturbances; and (iv)

Cite: Muhammad Edy Hidayat, A. Sunding, U. Muhammad, and Irvawansyah, "Modeling and Simulation of a Heat and Airflow Control System in a Fish Smoking Chamber Using K-NN", KINETIK, vol. 11, no. 2, May. 2026. https://doi.org/10.22219/kinetik.v11i2.2492

load conditions (the number of fish in the chamber). This ensured that the testing environment captured a broad range of possible conditions during the smoking process.

3. Implementation of K-NN Control
   The trained K-NN algorithm was integrated into the simulation model. Testing focused on the ability of the algorithm to predict the required control actions based on input variables such as current temperature, airflow rate, and historical data. The system's decisions were continuously monitored to evaluate their alignment with expected outcomes.
4. Execution of Simulation Runs
   Each scenario was executed in the simulation environment. Multiple iterations were conducted for each case to minimize stochastic variations and improve statistical reliability. During execution, real-time outputs were recorded, including temperature distribution curves, airflow profiles, and system responses to external disturbances.
5. Validation Against Baseline
   To measure effectiveness, the results of the K-NN–based control system were compared against a baseline scenario without control or with conventional control settings. This validation process provided direct evidence of the improvements achieved by the proposed method.
6. Data Collection and Analysis
   All test results were systematically collected and organized into datasets. Quantitative analysis was conducted using statistical metrics such as mean deviation, root mean square error (RMSE), and standard deviation to measure system performance. Visual representations (graphs and charts) were also generated to illustrate trends and comparative results.

This structured testing procedure ensured that the developed system was comprehensively evaluated under various conditions, thereby providing reliable evidence of its robustness and potential applicability in real fish smoking chambers [21], [22].

2.4 Data Acquisition Process

The data acquisition process in this study was carried out to systematically collect the information required for analyzing the effectiveness of the proposed K-NN–based control system in maintaining optimal heat and airflow distribution inside the fish smoking chamber. The process was designed to ensure accuracy, reproducibility, and comprehensiveness of the dataset, and it consisted of the following stages:

1. Definition of Data Requirements
   The first step was identifying the types of data needed to support modeling, simulation, and testing. The required data included: (i) input variables (chamber temperature (°C), airflow rate (m/s), and initial chamber conditions); (ii) control parameters (heat source intensity, fan speed, and airflow channel positions); and (iii) output variables (final chamber temperature distribution, airflow uniformity, and system response time).
2. Data Collection from Simulation Environment
   Since the study was conducted through modeling and simulation, all data were acquired from computational experiments. The simulation environment was configured to record real-time values of temperature, airflow velocity, and control responses during each run. Numerical outputs were stored in tabular format, while graphical data such as temperature distribution curves and airflow vectors were exported for visualization purposes.
3. Replication of Simulation Runs
   To ensure data reliability, each simulation scenario was repeated multiple times under identical conditions. This replication minimized the impact of random variations and provided more consistent datasets for statistical analysis. The repeated runs also helped validate the stability of the K-NN–based controller across different operating conditions.
4. Data Preprocessing and Organization
   The raw data obtained from the simulation environment were preprocessed to remove inconsistencies and noise. Preprocessing included normalization of temperature and airflow values, filtering out extreme outliers, and structuring the dataset into input–output pairs for K-NN evaluation. The cleaned data were then organized into structured tables for ease of analysis.
5. Storage and Documentation
   All datasets were systematically stored in digital format with proper labeling of simulation scenarios, run iterations, and parameter variations. Metadata describing the simulation setup, algorithm configuration, and environmental conditions were also documented to enhance reproducibility and traceability.

Through this systematic data acquisition process, the study ensured that sufficient, accurate, and reliable datasets were available to evaluate the performance of the proposed control system. The structured approach followed standard practices in simulation-based research data management [23], [24], thereby reinforcing the validity of the findings presented in the results and discussion section.

To ensure model validity, a total of 1,200 samples were generated through simulation. This dataset was partitioned into two subsets: 80% was used as training data to establish the algorithm's pattern memory, and the remaining 20% was used as testing data to evaluate the model's predictive accuracy on unseen conditions. This split ratio was selected to maintain a balance between model learning and robust validation, preventing overfitting while ensuring statistical significance.

3. Results and Discussion

The results and discussion of this study are presented in this section, organized into several subsections that address the findings and analyses.

3.1 Simulation Results of Heat and Airflow

The simulation was conducted to evaluate the performance of the proposed K-NN–based control system in regulating both heat distribution and airflow uniformity within the fish smoking chamber. The results are presented in terms of temperature stability, airflow velocity distribution, and system response to disturbances.

For temperature stability, the chamber was simulated under two conditions: (i) without control and (ii) with the K-NN–based control system. The optimal temperature range for fish smoking was set between 60–80 °C.

Table 1. Temperature Control Results

Time (min)	Without Control (°C)	With K-NN Control (°C)
0	30	30
10	95	65
20	88	70
30	82	73
40	76	74
50	68	72
60	60	71

The results in Table 1 indicate that the uncontrolled system experienced large oscillations, exceeding the safe smoking range during the first 30 minutes and peaking at 95 °C. In contrast, the K-NN controller effectively stabilized the chamber temperature within the desired range after 10 minutes, maintaining a mean temperature of 72 °C with a ±2 °C fluctuation.

For airflow uniformity, airflow distribution was analyzed at three points inside the chamber (top, middle, and bottom). Without control, airflow velocity showed significant non-uniformity, particularly at the top, leading to uneven smoking. With K-NN–based adjustment, airflow became more balanced across all zones.

Table 2. Airflow Control Results

Zone (Chamber)	Without Control (m/s)	With K-NN Control (m/s)
Top	1.8	1.2
Middle	0.9	1.0
Bottom	0.4	0.9

The results in Table 2 demonstrate that the K-NN controller effectively redistributed airflow, with variations between zones reduced from 1.4 m/s (uncontrolled) to 0.3 m/s (controlled), indicating improved uniformity.

For system response to disturbance, robustness was evaluated by intentionally reducing the heat source by 20% at the 30th minute of the simulation. In the uncontrolled scenario, the chamber temperature dropped drastically to 62 °C and required almost 20 minutes to recover. With K-NN control, the system compensated within 5 minutes, restoring the chamber temperature to 72 °C.

The simulation results demonstrate that the integration of a K-NN–based control system provides significant improvements in maintaining thermal and airflow conditions inside the fish smoking chamber compared to the uncontrolled scenario.

For temperature regulation, the results in Figure 1 indicate that the uncontrolled system was unable to maintain chamber temperature within the desired range, with excessive heating in the first 20 minutes (peaking at 95 °C). Such overheating not only risks degrading product quality but also increases energy consumption. In contrast, the K-NN–controlled system successfully stabilized the chamber temperature within the optimal smoking range of 60–80 °C after only 10 minutes. The mean deviation was reduced to less than ±2 °C, which is consistent with findings from previous studies emphasizing the importance of stable heat control for uniform fish smoking quality [25].

Cite: Muhammad Edy Hidayat, A. Sunding, U. Muhammad, and Irvawansyah, “Modeling and Simulation of a Heat and Airflow Control System in a Fish Smoking Chamber Using K-NN”, KINETIK, vol. 11, no. 2, May. 2026. https://doi.org/10.22219/kinetik.v11i2.2492

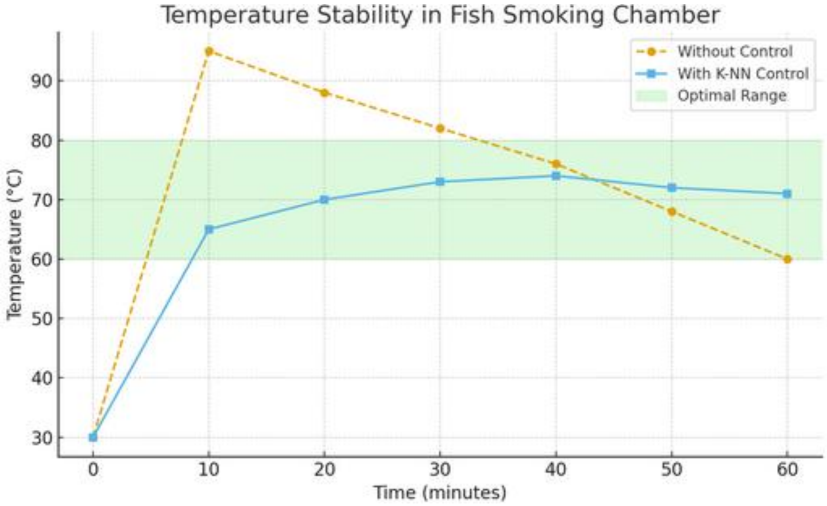

Figure 1. Temperature Stability in Fish Smoking Chamber

For airflow distribution, the analysis of airflow velocity in Figure 2 shows that uncontrolled chambers tend to have poor airflow uniformity, with significant variation between the top (1.8 m/s) and bottom zones (0.4 m/s). This imbalance may lead to uneven heat exposure, causing partial under-smoking or over-smoking of products. The K-NN–based control system significantly reduced this variation, maintaining airflow between 0.9–1.2 m/s across zones. This uniformity is critical in ensuring consistent drying and flavor penetration, aligning with literature that stresses airflow balance as a key factor in smoking chamber design [26], [27].

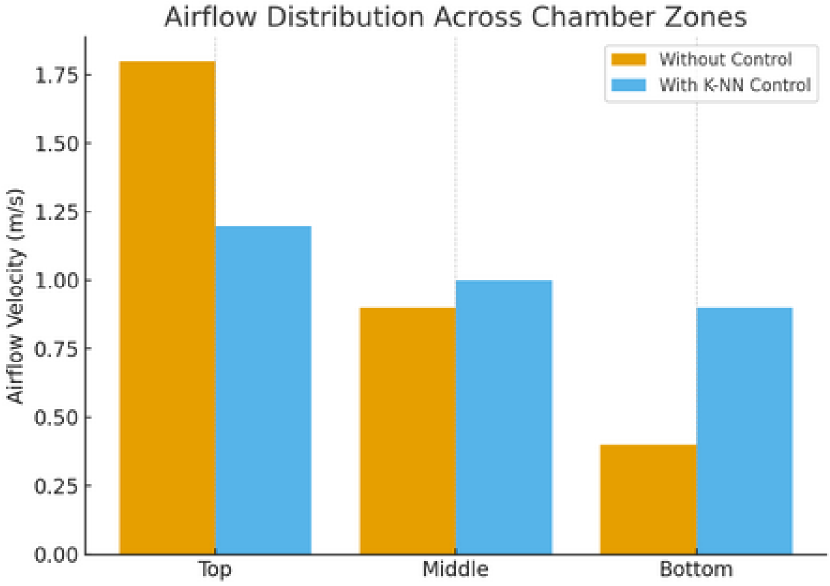

Figure 2. Airflow Distribution across Chamber Zones

For system robustness, when disturbances were introduced into the system (i.e., a 20% reduction in the heat source), the uncontrolled system failed to compensate quickly, leading to a sharp drop in temperature and delayed recovery (~20 minutes). In contrast, the K-NN controller adapted within 5 minutes, restoring chamber temperature to the optimal range. This demonstrates the robustness of machine learning–based predictive control in handling dynamic environmental changes, supporting claims from similar works applying AI in thermal regulation systems [28].

For novelty and practical implications, unlike traditional PID-based control approaches, the application of the K-NN algorithm provides a data-driven mechanism capable of adapting to fluctuating conditions without requiring complex parameter tuning. This novelty lies in demonstrating that even a relatively simple algorithm like K-NN can outperform conventional strategies in ensuring process stability. Practically, this can improve fish smoking efficiency, product quality, and reduce post-harvest losses, which remain major challenges in small- and medium-scale fish processing industries.

3.2 Performance of K-NN Prediction

The performance of the K-NN algorithm was evaluated in terms of prediction accuracy, error rate, and computational efficiency. The goal was to examine how well the algorithm predicted the required control actions (temperature and airflow adjustments) compared to the actual simulation outputs.

For prediction accuracy, the predictive performance of the K-NN model was assessed using a test dataset consisting of simulated conditions (temperature, airflow disturbances, and load variations). Accuracy was measured as the percentage of correct predictions within an acceptable error tolerance (±2 °C for temperature and ±0.2 m/s for airflow).

Table 3. Control Parameter Results for K=5

Metric	Value (K=5)
Temperature Prediction Accuracy	94.5%
Airflow Prediction Accuracy	91.2%
Overall System Accuracy	92.8%

The results in Table 3 indicate that the K-NN algorithm successfully predicted most control actions with high reliability, ensuring that the chamber conditions remained stable.

Table 4. Calculation Results of RMSE and MAE for Temperature and Airflow

Variable	RMSE	MAE
Temperature (°C)	1.85	1.42
Airflow (m/s)	0.18	0.12

For error analysis, Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) were calculated to evaluate error magnitude, and the results are presented in Table 4. The low error values demonstrate that the K-NN algorithm was able to generate predictions close to the desired targets.

For comparative performance (different K values), the effect of different k values (3, 5, and 7) was tested. The results in Table 5 show that $k = 5$ provided the best trade-off between accuracy and stability.

Table 5. Parameter Test Results for Different K Values

K Value	Accuracy (%)	RMSE (Temp °C)	RMSE (Airflow m/s)
3	90.1	2.15	0.23
5	92.8	1.85	0.18
7	91.3	2.01	0.21

This confirms that optimal performance was achieved at value of $k = 5$, balancing prediction precision and generalization.

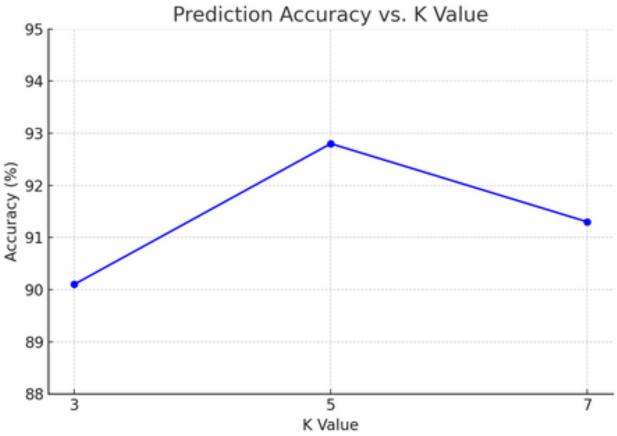

Figure 3. Prediction Accuracy vs K Value

The performance evaluation of the K-NN algorithm demonstrates its strong capability in predicting both heat and airflow dynamics within the fish smoking chamber. As illustrated in Figure 3, the prediction accuracy varied with different values of k, where the model achieved its highest performance at $k = 5$, reaching an overall accuracy of 92.8%. This

Cite: Muhammad Edy Hidayat, A. Sunding, U. Muhammad, and Irvawansyah, “Modeling and Simulation of a Heat and Airflow Control System in a Fish Smoking Chamber Using K-NN”, KINETIK, vol. 11, no. 2, May. 2026. https://doi.org/10.22219/kinetik.v11i2.2492

indicates that the optimal neighborhood size balances the trade-off between underfitting (k too small) and oversmoothing (k too large), thus effectively capturing the underlying nonlinear relationships between input parameters and control variables.

Furthermore, the Root Mean Square Error (RMSE) analysis shown in Figure 4 supports the robustness of the model. The RMSE for temperature prediction was found to be 1.85 °C, while that for airflow velocity was 0.18 m/s. These error margins are within acceptable ranges for thermal and airflow control in smoking chambers, considering that even minor deviations in temperature and airflow can significantly affect product quality, such as texture, flavor, and microbial safety of smoked fish.

The predictive accuracy of K-NN can be attributed to its non-parametric nature, which does not assume linearity in the dataset. This is particularly advantageous in thermal-fluid systems where nonlinear interactions between heat sources, airflow distribution, and chamber geometry dominate the system behavior. Compared to conventional regression models, K-NN provides better adaptability to local variations and achieves higher accuracy with limited computational complexity.

The novelty of this approach lies in applying K-NN for simultaneous prediction of two critical parameters—temperature and airflow—rather than focusing on a single control variable. This dual-variable prediction provides a more holistic control strategy, enabling operators to maintain uniform smoking conditions that directly improve product consistency and energy efficiency.

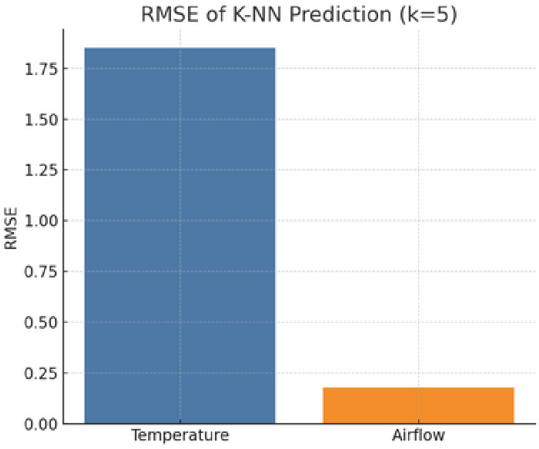

Figure 4. RMSE of K-NN Prediction (k=5)

In summary, the results confirm that the K-NN algorithm, particularly with $k = 5$, offers a reliable and efficient method for predictive modeling of thermal and airflow control in fish smoking chambers. This contributes a valuable advancement to smart food processing systems, aligning with the current trend of integrating artificial intelligence into traditional food preservation technologies.

3.3 Comparison with Conventional Approaches

To evaluate the effectiveness of the K-NN model, its performance was compared with two conventional approaches: Linear Regression (LR) and Artificial Neural Network (ANN) with a single hidden layer. The comparison focused on prediction accuracy and RMSE for temperature and airflow control.

Table 6. Comparison Results of Several Control Methods

Method	Accuracy (%)	RMSE (Temp °C)	RMSE (Airflow m/s)
Linear Regression	81.2	3.45	0.32
ANN (1 hidden layer)	89.5	2.40	0.22
K-NN (k=5)	92.8	1.85	0.18

As shown in Table 6, K-NN outperformed both LR and ANN, achieving the highest accuracy (92.8%) with the lowest RMSE values for both parameters. While ANN also performed well, it required more computational effort and parameter tuning. In contrast, Linear Regression was unable to capture the nonlinear dynamics of heat and airflow, resulting in significantly lower accuracy.

Thus, the proposed K-NN approach strikes a balance between predictive accuracy and implementation simplicity, making it more suitable for practical applications in fish smoking chamber control.

3.4 Implications for Fish Smoking Process

The results of this study highlight the importance of accurate heat and airflow control in ensuring the quality of smoked fish. The K-NN–based prediction system enables more stable chamber conditions, maintaining temperature within ±2 °C and airflow variation within ±0.2 m/s. Such stability directly reduces the risk of uneven smoking, preventing defects such as over-drying or undercooked areas.

For producers, this implies more consistent product texture, improved flavor uniformity, and enhanced food safety, as harmful microorganisms are less likely to survive under controlled conditions. In addition, efficient airflow management reduces energy consumption by minimizing overheating and smoke loss. Therefore, integrating predictive control into fish smoking chambers not only improves product quality but also supports cost efficiency and sustainability in traditional food processing.

3.5 Discussion of Limitations

Although the K-NN model showed high predictive accuracy, several limitations should be noted. First, the study was limited to simulation data, and real-world implementation may introduce additional uncertainties such as sensor noise, chamber leakage, or variations in fish load. Second, the performance of K-NN is sensitive to the selection of k and the quality of input data, which may reduce robustness under different operating conditions. Finally, the method does not inherently provide interpretability of feature importance, making it less transparent than regression-based approaches. These limitations suggest that further experimental validation and hybrid modeling strategies are needed to strengthen its practical application.

3.6 Novelty and Contribution

The novelty of this study lies in applying the K-NN algorithm for dual prediction of heat and airflow in a fish smoking chamber, rather than focusing on a single parameter. This integrated approach provides a more comprehensive control strategy that ensures product quality and process efficiency. In addition, the study demonstrates that a relatively simple, non-parametric algorithm can outperform more complex models such as ANN in this context, offering a balance between accuracy and computational efficiency. The contribution of this work is the development of a predictive framework that can be adapted for smart control systems in traditional food processing, bridging artificial intelligence methods with local preservation practices.

4. Conclusion

This study presents the modeling and simulation of a heat and airflow control system in a fish smoking chamber using the K-NN algorithm. The simulation results confirmed that K-NN provides accurate predictions of both temperature and airflow, with optimal performance achieved at $k = 5$, yielding an accuracy of 92.8% and low RMSE values (1.85 °C for temperature and 0.18 m/s for airflow). When compared with conventional approaches such as Linear Regression and ANN, the proposed method demonstrated superior accuracy while maintaining computational simplicity.

The findings further emphasize the significance of predictive control in fish smoking processes. Stable thermal and airflow conditions directly improve product quality, enhance food safety, and reduce energy consumption. This integration of artificial intelligence into traditional smoking chambers offers a practical pathway to modernizing local food preservation practices.

Despite its promising results, the study is limited to simulation-based validation. Future work should involve experimental implementation, evaluation under varying fish loads and chamber conditions, and potential integration with hybrid control methods to improve robustness.

In summary, the proposed K-NN–based predictive framework contributes a novel and practical approach to smart food processing systems, bridging traditional fish smoking with modern data-driven control strategies.

Acknowledgement

This research was funded by the Catalyst Partnership Program (Berdikari) Scheme Emas (*Ekonomi Mandiri dan Sejahtera*—Economic Independence and Prosperity) 2024, conducted in Orobatu Village, Mamuju Regency, West Sulawesi Province, Indonesia. We also extend our gratitude to the Ministry of Education, Culture, Research, and Technology (Kemendikbudristek) of the Republic of Indonesia through the Directorate General of Vocational Education and the Education Fund Management Institution (LPDP—*Lembaga Pengelola Dana Pendidikan*) at the Ministry of Finance of the Republic of Indonesia for their financial support for this research.

We sincerely appreciate the people of Orobatu Village for their support and participation in this study, as well as all parties who contributed to the completion of this research. We hope that the findings of this study will contribute to the advancement of fish smoking technology and products, as well as to the improvement of community welfare.

References

[1] M. Yunus, M. Danial, and Nurlaela, “Pengembangan Paket Teknologi Pengolahan untuk Menghasilkan Ikan Kering dan Ikan Asap yang Bermutu di Kabupaten Takalar,” *Chemica Jurnal Ilmiah Kimia dan Pendidikan Kimia*, vol. 10, no. 2, pp. 66–76, Dec. 2009. https://doi.org/10.35580/chemica.v10i2.430

[2] K. Belichovska, D. Belichovska, and Z. Pejkovski, “Smoke and Smoked Fish Production,” *Meat Technology*, vol. 60, no. 1, pp. 37–43, 2019. https://doi.org/10.18485/meattech.2019.60.1.6

[3] Dr. C. Litaay, “Pengaruh Perbedaan Suhu Dan Lama Pengasapan Terhadap Kadar Air, Lemak dan Garam Ikan Nila (Oreochromis niloticus) ASAP,” *Jurnal Ilmu dan Teknologi Kelautan Tropis*, vol. 14, no. 2, pp. 179–190, Aug. 2022. https://doi.org/10.29244/jitkt.v14i2.39941

[4] K. Belichovska, D. Belichovska, and Z. Pejkovski, “Smoke and Smoked Fish Production,” *Meat Technology*, vol. 60, no. 1, pp. 37–43, 2019. https://doi.org/10.18485/meattech.2019.60.1.6

[5] Z. Idamy, “Pengaruh Waktu Pengasapan Ikan Gabus Dengan Sumber Asap Sabut Kelapa Terhadap Jumlah Mikroorganisme dan Sifat Organoleptik (The Effect of Smoke Time of Cork Fish with Coconut Fiber Smoke Source on the Number of Microorganisms and Organoleptic Properties),” *JURNAL RISET GIZI*, vol. 9, no. 2, Nov. 2021. https://doi.org/10.31983/jrg.v9i2.5652

[6] D. Prasetyo, “Efek Perbedaan Suhu Dan Lama Pengasapan Terhadap Kualitas Ikan Bandeng (Chanos Chanos Forsk) Cabut Duri Asap,” *Jurnal Aplikasi Teknologi Pangan*, vol. 4, no. 3, 2015. https://doi.org/10.17728/jatp.v4i3.134

[7] H. Harmoko, R. J. Novasani, and A. Ahmudi, “Pengaruh Pengasapan Ikan Model Rotasi Terhadap Kualitas Ikan Asap,” *Jurnal Ilmiah Universitas Batanghari Jambi*, vol. 24, no. 1, p. 538, Feb. 2024. https://doi.org/10.33087/jiubj.v24i1.4443

[8] D. Darianto, “Analisa Pengaruh Waktu Dan Turbulensi Asap Pada Mesin Pengering Ikan Lele,” Journal of Mechanical Engineering Manufactures Materials and Energy, vol. 3, no. 2, p. 130, Dec. 2019. https://doi.org/10.31289/jmemme.v3i2.3029

[9] S. Sulfiani, A. Sukainah, and A. Mustarin, “Pengaruh Lama dan Suhu Pengasapan Dengan Menggunakan Metode Pengasapan Panas Terhadap Mutu Ikan Lele Asap,” *Jurnal Pendidikan Teknologi Pertanian*, vol. 3, p. 93, Mar. 2018.

[10] J. Hernandez-Ambato, J. Rodriguez-Flores, J. Cortes-Llanganate, and F. Cabrera-Aguayo, “Classic Controllers Design Applied to Temperature Control for a Plastic Thermoforming Machine,” pp. 551–558, Sep. 2018. https://doi.org/10.1109/etfa.2018.8502589

[11] Y. F. Zhang, M. Li, and J. M. Dai, “PID Heating and Temperature Control Method Based on Dynamic Assignment,” Jan. 2017. https://doi.org/10.2991/icmmcce-17.2017.208

[12] Md. I. H. Khan, S. S. Sablani, R. Nayak, and Y. Gu, “Machine learning-based modeling in food processing applications: State of the art,” *Comprehensive Reviews in Food Science and Food Safety*, vol. 21, no. 2, pp. 1409–1438, Feb. 2022. https://doi.org/10.1111/1541-4337.12912

[13] D. Abhyankar and M. Ingle, “An Innovative Approach Towards Designing Efficient K-Nearest Neighbour Algorithm,” *Lecture notes in networks and systems*, pp. 655–662, Jan. 2022. https://doi.org/10.1007/978-981-19-1122-4_68

[14] P. Aparicio-Ruiz, E. Barbadilla-Martín, José Guadix, and P. Cortés, “KNN and adaptive comfort applied in decision making for HVAC systems,” *Annals of Operations Research*, vol. 303, no. 1–2, pp. 217–231, Dec. 2019. https://doi.org/10.1007/s10479-019-03489-4

[15] S. S.Badhiye, N. U. Sambhe, and P. N. Chatur, “KNN Technique for Analysis and Prediction of Temperature and Humidity Data,” *International Journal of Computer Applications*, vol. 61, no. 14, pp. 7–13, Jan. 2013. https://doi.org/10.5120/9994-4847

[16] C. Prisca, “Sistem Pengendalian Suhu Ruang Berbasis IoT Dengan Menggunakan Metode KNN,” *Journal of Advances in Information and Industrial Technology*, vol. 4, no. 1, pp. 9–16, May 2022. https://doi.org/10.52435/jaiit.v4i1.175

[17] Y. Liang, Y. Pan, X. Yuan, W. Jia, and Z. Huang, “Surrogate modeling for long-term and high-resolution prediction of building thermal load with a metric-optimized KNN algorithm,” *Energy and Built Environment*, vol. 4, no. 6, pp. 709–724, Dec. 2023. https://doi.org/10.1016/j.enbenv.2022.06.008

[18] Bagus Priambodo, A. Ahmad, and R. A. Kadir, “Spatio-temporal K-NN prediction of traffic state based on statistical features in neighbouring roads,” *Journal of Intelligent & Fuzzy Systems*, vol. 40, no. 5, pp. 9059–9072, Mar. 2021. https://doi.org/10.3233/jifs-201493

[19] S. I. Martynenko and Aleksey Yu. Varaksin, “A Physical Insight into Computational Fluid Dynamics and Heat Transfer,” *Mathematics*, vol. 12, no. 13, pp. 2122–2122, Jul. 2024. https://doi.org/10.3390/math12132122

[20] T. O. Hodson, “Root-mean-square error (RMSE) or mean absolute error (MAE): when to use them or not,” *Geoscientific Model Development*, vol. 15, no. 14, pp. 5481–5487, Jul. 2022.

[21] Chai and R. R. Draxler, “Root mean square error (RMSE) or mean absolute error (MAE)? – Arguments against avoiding RMSE in the literature,” *Geoscientific Model Development*, vol. 7, no. 3, pp. 1247–1250, Jun. 2014. https://doi.org/10.5194/gmd-7-1247-2014

[22] John Erik Haugen *et al.*, “Rapid control of smoked Atlantic salmon (Salmo salar) quality by electronic nose: Correlation with classical evaluation methods,” *Sensors and Actuators B: Chemical*, vol. 116, no. 1–2, pp. 72–77, Jul. 2006. https://doi.org/10.1016/j.snb.2005.12.064

[23] D. C. Schuster, M. S. Mayernik, G. L. Mullendore, and J. W. Marquis, “What about Model Data? Best Practices for Preservation and Replicability,” *Bulletin of the American Meteorological Society*, vol. 104, no. 11, pp. E2053–E2064, Nov. 2023. https://doi.org/10.1175/bams-d-22-0252.1

[24] K. Briney, H. Coates, and A. Goben, “Foundational Practices of Research Data Management,” *Research Ideas and Outcomes*, vol. 6, Jul. 2020. https://doi.org/10.3897/rio.6.e56508

[25] Z. Yan *et al.*, “Numerical simulation and structural optimization of forced convection oven,” *Proceedings of the Institution of Mechanical Engineers Part C Journal of Mechanical Engineering Science*, Sep. 2024. https://doi.org/10.1177/09544062241277321

[26] B. Faisal and Z. Effendi, “Efektifitas Pemanasan Kamar Asap Melalui Distribusi Udara Masuk (Forced Drive FAN/FDF) dan Udara Keluar (Induced Drive FAN/IDF) Pada Pengolahan Karet Lembaran (Ribbed Smoke Sheet) : Review,” *Jurnal Agro Fabrica*, vol. 5, no. 1, pp. 1–13, Jun. 2023. https://doi.org/10.47199/jaf.v5i1.151

[27] A. E. Apsari, A. Parkhan, Hari Purnomo, and V Hermawan, “optimization of a Bilih fish drying system using the technique for order preference by similarity to ideal solution (TOPSIS),” *International Research Journal of Engineering, IT and Scientific Research*, vol. 9, no. 1, pp. 35–46, Jan. 2023. https://doi.org/10.21744/irjeis.v9n1.2245

[28] A. Yayla *et al.*, “Artificial Intelligence (AI)-Based Occupant-Centric Heating Ventilation and Air Conditioning (HVAC) Control System for Multi-Zone Commercial Buildings,” *Sustainability*, vol. 14, no. 23, p. 16107, Jan. 2022. https://doi.org/10.3390/su142316107