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System identification of batch milk cooling using output error models

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ABSTRACT

Accurate modelling of milk cooling dynamics is essential to maintain product quality and improve energy efficiency in small-scale dairy operations. This study aims to develop a dynamic model for a batch milk-cooling system used at *Koperasi Unit Desa Sinau Andandani Ekonomi* (KUD SAE) Pujon. Synthetic temperature data were generated under controlled perturbations reflecting actual process conditions, and the data were analysed using the output error (OE) identification method implemented in the MATLAB System Identification Toolbox. Several OE model structures were compared using statistical indicators, including the coefficient of determination (R^2) and root mean square error (RMSE). The OE (2,2,1) model achieved the best performance with $R^2 = 0.9923$ and RMSE = 0.0600, accurately representing the first-order dynamics of the cooling process. The identified model provides a reliable foundation for process optimisation, controller design, and operator training in dairy systems. Although the validation is limited to simulated data, the proposed approach offers substantial potential for real-time implementation and can be extended to other temperature-sensitive food processes.

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1. INTRODUCTION

Milk is a highly perishable, nutrient-rich liquid that provides an ideal environment for microbial growth if not cooled immediately after milking. Effective cooling to approximately 4 °C within four hours is essential to inhibit pathogenic microorganisms and spoilage, maintain sensory quality, and extend shelf life. In Indonesia, dairy cooperatives such as *Koperasi Unit Desa Sinau Andandani Ekonomi* (KUD SAE) Pujon use batch cooling twice daily to maintain quality before shipment to processing facilities. Milk cooling requires significant energy, typically involving initial cooling with water followed by refrigeration. Optimising this process can significantly reduce operational costs and environmental impact. While studies have investigated cooling equipment, energy recovery, and control methods, few have focused on developing an accurate dynamic model of the milk-cooling process itself.

This research aims to fill this gap by applying the output error (OE) method to model batch milk cooling, validating the model using simulated data, and demonstrating its application in process optimisation, control system design, and operator training.

The primary reason for cooling milk is to prevent the growth of pathogenic and spoilage microorganisms, which can rapidly multiply in warm milk. The cooling process ensures that the milk reaches a safe temperature (typically around 4 °C), slowing microbial activity and preserving its quality of the milk. Failure to cool milk efficiently can lead to:

– Increased bacterial counts, which can cause spoilage, unpleasant odours, and taste.
– Compromised safety by allowing harmful pathogens to multiply, potentially leading to foodborne illnesses.
– Deterioration of milk's nutritional and sensory qualities, such as protein breakdown, which affects texture and shelf life.

In Indonesia, KUDs (cooperatives) provide facilities to maintain quality by ensuring hygienic storage and cooling of milk before it is transported to milk factories [1]. This is necessary because cattle farms are sometimes far from processing factories and markets.

Cooling raw milk soon after milking – within a maximum of four hours (maximal) - is known as the most cost-effective and best method to avoid spoilage and maintain quality [2], [3]. Therefore, it is typically carried out in KUDs as a batch cooling process twice a day, usually in the morning and evening. However, more advanced treatments are available, such as high temperature short time (HTST) / thermosonication, low temperature long time (LTLT), and ultra high temperature (UHT) [4].

The use of electricity for the milk refrigeration process is quite extensive [5], hence dairy product processes are energy-intensive [6]. Milk may be cooled in two stages: first, initial cooling, then cooling with refrigerant to approximately 4 °C. The cost associated with cooling in dairy cooling centres can be reduced by cooling raw milk using water at room temperature. Precooling decreases the cooling burden, thereby reducing energy and cost requirements. A discernible temperature differential between fresh raw milk and the water can save cooling costs by up to 64% [1]. The chilling system's efficiency and the temperature difference between the initial and final states significantly affect the total energy required for cooling [7].

The milk within the tank can be gradually cooled using chilled water. A water chiller (or an ice bank) can be used to cool this water, typically consisting of an evaporator, a condenser, a refrigerant unit, and a water tank insulated with a storage unit. The water is then cooled to around 1 °C, which subsequently lowers the milk's temperature to approximately 4 °C [8]. Water can also be cooled by passing it through an ice bank system. In a closed-loop cycle, water circulates through the storage tank and returns to the ice bank as ice forms around the copper elements [8].

Feedback control and feedforward control for a milk chilling system, involving precooling and refrigerant cooling, were studied, and the controllers were tuned using Ziegler Nichols ultimate gain method has also been studied [7]. However, no information for the plant model is given. A basic method for obtaining a mathematical model for a mercury thermometer was presented [9] and adopted here because of its similarity in nature [10].

A study on recovering waste heat from a large-scale milk cooling system has also been conducted [11]. To increase the facility's energy efficiency, the heat released into the environment by the condenser was recaptured. The water heated by this waste heat can then be used to clean the milk-processing machinery. Another study was focused on ice banks for milk cooling after milking [8]. However, few models were found that specifically discussed the milk cooling process itself. A different method of system identification using auto regressive exogenous (ARX) has also been reported [12].

The primary objectives of this research are to develop an OE model that accurately represents the milk cooling process, validate the model using simulated experimental data, and demonstrate its practical applications in process design, operator training, safety system analysis, and control system design. By addressing these objectives, the study aims to provide a comprehensive framework for improving milk-cooling operations in dairy facilities [9]. The research was conducted at the KUD SAE Pujon milk cooling facility, where significant variations in cooling efficiency were observed. The findings of this research are expected to contribute to the broader field of dairy process engineering, offering insights applicable to similar processes in other food industries.

2. METHOD

This study analyses a batch milk cooling system at the KUD SAE Pujon, consisting of a half-cylindrical milk container immersed in a rectangular cold-water tank. The governing equations were derived from heat-balance principles, and the system parameters were measured on-site. Simulation data were generated using MATLAB/Simulink. The OE method was employed for system identification using the MATLAB System Identification Toolbox. Input–output datasets were obtained by introducing controlled perturbations to the cold-water temperature (input) and recording the resulting milk temperature (output). Several OE model structures were estimated and compared based on goodness-of-fit criteria. Validation was performed through visual inspection, statistical analysis (mean squared error (MSE), root mean square error (RMSE), and coefficient of determination (R^2)), cross-validation, and robustness tests under varying disturbances.

2.1. Materials and governing equation

The study focused on a milk cooling apparatus used by KUD SAE Pujon [10] as illustrated in Figure 1. This system comprised a rectangular cooling tank that housed a semi-cylindrical milk container. Specifically, the semi-cylindrical container held the milk, while the rectangular tank served as a reservoir for the chilling water. A schematic of this milk chilling setup is shown in Figure 2.

Figure 1. Milk cooling equipment at Pujon-Malang

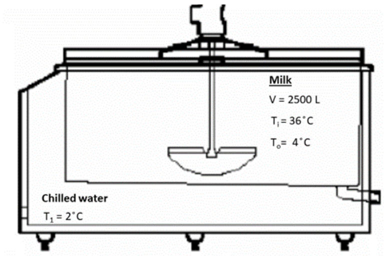

Figure 2. Side view of milk cooling system

The transfer function model for batch milk chilling process had been obtained based on energy conservation law and [10] resulting the (1).

$$G(s) = \frac{T_o(s)}{T_1(s)} = \frac{1}{\frac{m.C_p}{U.A}s+1} \tag{1}$$

$G(s)$ in s domain is a transfer function (1st order in Laplace transformation) with:

$$Time\ constant = \frac{m.C_p}{U.A} \tag{2}$$

and

$$Gain = 1 \tag{3}$$

The data used for this simulation (batch condition and parameter) is shown in Table 1.

Table 1. Parameter data

Symbol	Parameters	Values	Units
V	Tank volume	2,5	m^3
r	Radius of a semicircular cylinder	0.3845	m
t	Length of a semicircular cylinder	1.238	m
T_i	Inlet milk temperature	36.00	°C
T_o	Milk temperature inside the tank	4.00	°C
T_1	Chilled water temperature	2.00	°C
C_p	Milk heat capacity	3.93	KJ/Kg.K
ρ	Milk density	1,027.00	Kg/m^3
m	Mass of milk in the tank	2,567.50	Kg
U	Overall heat transfer coefficient	274.461	KJ / (m^2 °C mins)
A	Surface area	0.8680	m^2
Q	Energy transmitted to chilled water	2,690.74	kJ/min

The semicircular cylinder's area is represented by the surface area (A) which can be computed using the values of r and t:

$$A = \frac{1}{2}\pi.r(r+t) = 0.8680\ m^2 \tag{4}$$

Given its 2.5 m^3 volume, and the knowledge of the milk's density (ρ), the mass of the milk within the tank (m) could be determined.

ΔT_{LMTD} (Log mean temperature difference) for milk cooling process [13]-[15] is:

$$\Delta T_{LMTD} = \frac{\Delta T_2 - \Delta T_1}{ln\left(\frac{\Delta T_2}{\Delta T_1}\right)} = 11.2946 \text{ °C} \quad (5)$$

Given the condition that $Q = U \times A \times \Delta T_{LMTD}$; therefore:

$$U = 274.461 \text{ KJ / (m}^2 \text{ °C mins)} \quad (6)$$

For 2 hours cooling time then the energy that should be transmitted to chilled water could be calculated as (7).

$$Q = m \times C_p \times \Delta T = 2{,}690.74 \text{ KJ/min} \quad (7)$$

2.2. OE method

Process modelling approaches can be broadly classified into two main categories: model-driven methods and data-driven method [16]. System identification is widely used across engineering disciplines to develop models from empirical data [17]-[19]. Many empirical techniques necessitate the initial selection of a model structure, after which model parameters are identified using appropriate methods. The least squares method is a commonly used approach for this purpose [20], [21]. Suppose a process with output subject to an input where k represents a discrete time value. Suppose that the signal can be associated with a linear process, the following equation can be written [22]:

$$A(z^{-1}) \times y(k) = \frac{B(z^{-1})}{F(z^{-1})} \times u(k-p) + \frac{C(z^{-1})}{D(z^{-1})} \times e(k) \quad (8)$$

Here z^{-1} represents the shift operator and is defined as (9):

$$y(k-1) = z^{-1} \times y(k) \quad (9)$$

The polynomials (A to D and F) are provided as (10)-(14) [23]:

$$A(z^{-1}) = 1 + a_1 \times z^{-1} + \ldots + a_{na} \times z^{-na} \quad (10)$$

$$B(z^{-1}) = b_0 + b_1 \times z^{-1} + \ldots + b_{nb} \times z^{-nb} \quad (11)$$

$$C(z^{-1}) = c_0 + c_1 \times z^{-1} + \ldots + c_{nc} \times z^{-nc} \quad (12)$$

$$D(z^{-1}) = d_0 + d_1 \times z^{-1} + \ldots + d_{nd} \times z^{-nd} \quad (13)$$

$$F(z^{-1}) = f_0 + f_1 \times z^{-1} + \ldots + f_{nf} \times z^{-nf} \quad (14)$$

At the same time, p denotes the sampling interval for both the input and output of the process while e represents the modeling error [24].

In the literature [25], the layout of the OE model depicted in Figure 3 can be expressed as (15):

$$y(k) = \frac{B(z^{-1})}{F(z^{-1})} \times u(k-p) + e(k) \quad (15)$$

This implies that $n_a = 0$, $n_c = 0$, and $n_d = 0$.

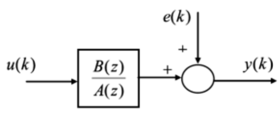

Figure 3. Output error model structure

The approach of process identification through input-output measurement is commonly applied in scenarios where an in-depth mathematical understanding of the system under study is not essential. Instead, it suffices to analyse the system's dynamics [26]-[28]. Black-box modelling can additionally capture the nonlinear dynamics of the plant, facilitating process monitoring and control, albeit without elucidating the physical mechanisms underlying the process behaviour [29].

The research method employed involves several key steps:

a. Data collection: data were collected by introducing controlled perturbations into the input (chilled water temperature) and recording the output (milk temperature).
b. Model selection: various OE models were selected to capture the system's dynamics. The selection of these models was based on their ability to fit the experimental data accurately.
c. Model validation: the models were validated by comparing their predictions against actual system responses to different perturbations. The validation process included visual inspection of the fit and numerical assessment of the model parameters.

By carefully explaining the data collection, model selection, and validation processes, the research provided a clear and thorough understanding of the system's dynamics and the effectiveness of the OE models in predicting milk cooling behaviour. Future research should integrate the OE model with advanced control strategies, such as model predictive control (MPC) [30]-[33] or adaptive control [34]-[37], to enable real-time optimisation of milk refrigeration. Extending this modelling approach to other temperature-sensitive food processes could further enhance its industrial relevance.

3. RESULTS AND DISCUSSION

The dynamic behaviour of the batch milk cooling process was first represented using a mechanistic transfer function derived from energy balance. By substituting the measured parameters of milk mass (m), heat capacity (Cp), overall heat transfer coefficient (U), and surface area (A) into the governing equations, the following first-order transfer function was obtained:

$$G(s) = \frac{1}{\tau s+1} = \frac{1}{42.3548s+1} \tag{16}$$

This equation represents the temperature dynamics of milk approaching equilibrium with the cooling medium, where τ denotes the system time constant. Simulation using MATLAB/Simulink confirmed that the milk temperature asymptotically reaches 4 °C within approximately two hours, consistent with typical field operation at the KUD SAE Pujon [10], [12].

To assess the dynamic response to perturbations, controlled variations in chilled water temperature were applied Figure 4, and the resulting milk temperature profile was recorded Figure 5. These data formed the basis for system identification using several OE model structures. The identified OE models displayed in Table 2: OE111, OE121, and OE221 were then validated using separate perturbation datasets Figures 6 to 8.

The results demonstrated that all three OE models were capable of capturing the dynamic behaviour of the cooling process; however, their accuracy varied depending on model order and complexity. Quantitative validation metrics are summarised in Table 3. The OE221 model achieved the highest accuracy with $R^2 = 0.9923$ and RMSE = 0.0600, followed by OE121 and OE111, confirming that a higher-order model structure yields a more precise dynamic representation.

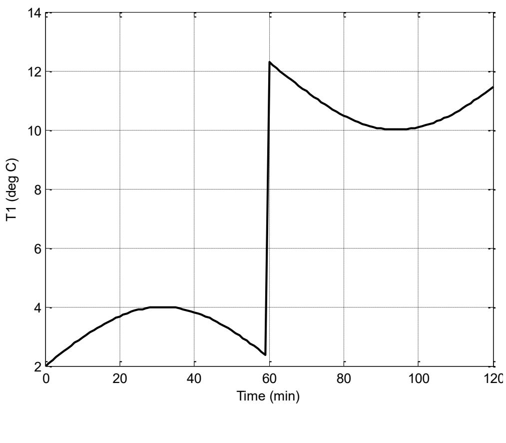

Figure 4. Perturbation of the chilled water temperature

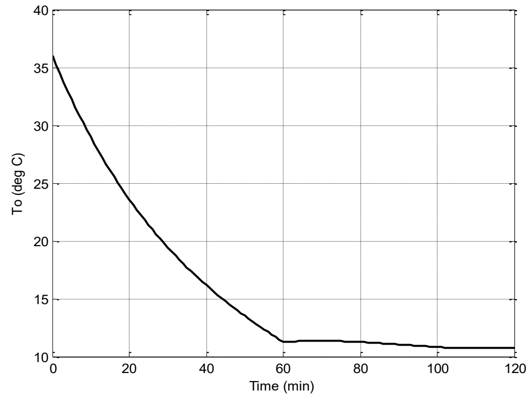

Figure 5. Milk temperature

Table 2. OE models

Model	Discrete transfer function	Continuous transfer function
OE221	$\frac{0.02249z^{-1} - 0.01344z^{-2}}{1 - 1.159z^{-1} - 0.5989z^{-2}}$	$\frac{0.02252s + 0.01158}{s^2 + 0.5127s + 0.01158}$
OE111	$\frac{0.01992z^{-1}}{1 - 0.9809z^{-1}}$	$\frac{0.02011}{s + 0.0193}$
OE121	$\frac{0.01007z^{-1}}{1 - 1.544z^{-1} + 0.5545z^{-2}}$	$\frac{0.006025s + 0.01334}{s^2 + 0.5897s + 0.01339}$

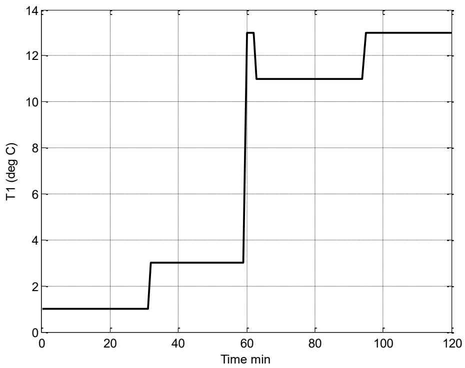

Figure 6. Perturbation of the chilled water temperature for model testing

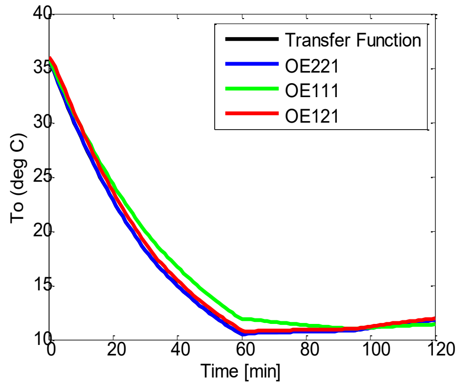

Figure 7. Milk temperature profile due to perturbation in Figure 6

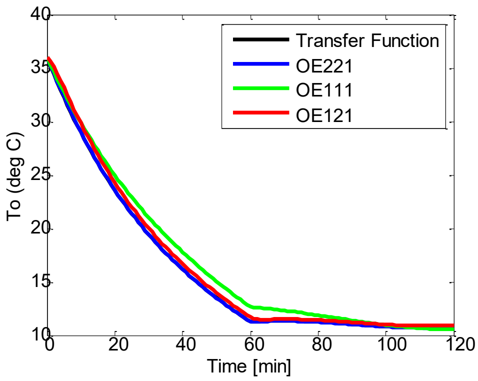

Figure 8. Milk temperature profile due to perturbation in Figure 4

Table 3. Results of statistical analysis

Model	MSE	RMSE	R^2
OE221	0.003600	0.0600	0.9923
OE121	0.007566	0.0870	0.9888
OE111	0.526100	0.7253	0.9068

The comparison highlights that OE221 (second order) had the closest fit to the actual system behaviour, suggesting its robustness in predicting the milk cooling process. However, the mechanical model derived from (16) shows that it must be first order.

To confirm that the optimal models OE221, OE121, and OE111 are accurate and can be used, the following steps were taken:

1) Validation against experimental data: the models were validated using experimental data obtained from perturbation tests. By comparing the predicted temperature profiles with the actual measurements, the accuracy of each model was assessed.
2) Goodness of fit metrics: quantitative metrics such as MSE, RMSE, and R^2 values were calculated to evaluate the goodness of fit. OE221 showed the lowest MSE and RMSE, and the highest R^2, indicating the best fit among the models.
3) Cross-validation: the models were subjected to cross-validation by splitting the data into training and testing sets. This ensured that the models were balanced with the initial dataset and generalised well to new data.
4) Robustness checks: the robustness of the models was tested by introducing different types of perturbations and observing the consistency of the model predictions. OE221 consistently provided accurate predictions across various scenarios, confirming its robustness.

The OE model was specifically selected for this study due to its strong performance in accurately identifying system dynamics, even in complex, nonlinear processes. While other system identification methods, such as the ARX model [12], have been applied to similar processes, the OE model offers greater accuracy in predicting system behaviour when handling measurement errors or perturbations. This is particularly important for processes such as milk cooling, where precise control is required to maintain product quality and optimise energy consumption. Additionally, the OE model has proven robust in dynamic environments where rapid and accurate adjustments to system inputs (e.g., temperature changes) are critical. This flexibility, combined with the strong validation metrics such as low RMSE and high R^2 values Table 3, made it the ideal choice over other alternatives.

The numbers in the OE model's name represent the structure of the polynomials used in the transfer function that defines the system's dynamics. Here's how they differ:

a. OE221 model

Structure: the OE221 model has two poles, two zeros, and one delay (hence the "2-2-1" designation). Features:

- Two poles: the system's response is more flexible, allowing for a more complex dynamic behaviour. It can model processes with two dominant time constants, thereby representing systems with both fast and slow dynamics.
- Two zeros: the inclusion of two zeros provides additional flexibility in shaping the system's transient response.
- One delay: the model assumes there is a delay between the input and the output, which is common in physical systems where it takes time for changes in input (e.g., cooling water temperature) to affect the output (e.g., milk temperature).
- Applications: OE221 is suitable for systems with complex dynamics and where precise control of both fast and slow response times is essential. It provided the best fit for the milk cooling system, as shown by its lowest RMSE and highest R^2 values.

b. OE121 model

Structure: the OE121 model has one pole, two zeros, and one delay. Features:

- One pole: the OE121 model includes one pole, meaning the system has a single dominant time constant. This makes it suitable for systems that exhibit a single exponential response, such as those with uniform cooling or heating rates.
- Two zeros: the model includes two zeros, providing additional flexibility in shaping the system's transient response.
- One delay: like OE221, it accounts for a delay between the input and output.

- Applications: OE121 may be used in systems where the dynamics are less complex but where two transient response characteristics (due to two zeros) still need to be modelled. It is less accurate than OE221, but it may still offer a reasonable balance between accuracy and complexity.

c. OE111 model

Structure: the OE111 model has one pole, one zero, and one delay. Features:

- One pole: this represents the simplest form of the OE model, with only one time constant, making it suitable for systems where a single dynamic behaviour dominates.
- One zero: it provides limited flexibility in shaping the transient response, so it may not capture all the nuances of more complex systems.
- One delay: similar to the other models, it assumes a delay between input and output.
- Applications: OE111 is helpful for straightforward systems where a first-order dynamic (single time constant) with a delay is sufficient. However, for the milk cooling process, this model performed the worst in terms of fit, with a much higher RMSE (0.7253) and lower R^2 (0.9068).

By employing these validation techniques and statistical analyses, we can confidently state that the OE221, OE121, and OE111 models are accurate and reliable for predicting the milk cooling process under varying conditions. In summary:

- OE221 is the most complex and flexible model, capturing more dynamic behaviour with two time constants, making it highly accurate for processes like milk cooling.
- OE121 offers a balance between simplicity and flexibility, with one dominant time constant but still accounting for two transient characteristics.
- OE111 is the simplest model, capturing fundamental system dynamics with a single time constant, and is less suitable for complex systems like milk cooling.

The OE221 model was ultimately chosen for this study because it provided the most accurate representation of the milk cooling process, ensuring efficiency and consistency.

Physical Interpretation

The inherent multi-time-constant nature of milk cooling can explain the superior performance of the OE221 model. The process involves two dominant dynamic phenomena: (i) fast dynamics associated with external heat transfer between the milk surface and chilled water, governed by convection; and (ii) slow dynamics associated with internal heat conduction within the milk bulk.

The two poles in the OE221 model effectively capture these parallel mechanisms. At the same time, the inclusion of two zeros provides flexibility to represent transient nonlinearities such as boundary-layer resistance and changing temperature gradients. In contrast, simpler models (OE111 and OE121) cannot fully capture the delayed, nonuniform temperature response, resulting in higher residual errors.

Practical Implications

The identified OE221 model provides an accurate and computationally efficient basis for several practical applications:

- Control system design: the model can be directly integrated into the development of predictive or adaptive controllers, improving cooling rate precision and minimising compressor energy use.
- Process optimisation: the model enables energy-efficiency assessment by quantifying the dynamic response to varying cooling-water temperatures, aiding in determining optimal operating conditions.
- Operator training and fault detection: the dynamic behaviour captured by the model allows operators to anticipate deviations in process temperature, enhancing safety and product quality.

Summary of Validation

The comparison between the mechanistic and OE-based models confirmed that while the mechanistic transfer function adequately describes general trends, data-driven models such as OE221 provide higher fidelity when transient variations and nonlinear heat transfer effects are significant. The excellent agreement between simulated and predicted temperature profiles Figures 6–8 validates the robustness of the OE221 model in representing batch milk-cooling dynamics under varying disturbances.

4. CONCLUSION

This study developed and validated a data-driven OE model for the batch milk cooling process at the SAE Pujon Cooperative. The OE-based modelling framework provides a reliable and interpretable foundation for optimising cooling system performance, energy use, and product quality in dairy process engineering. Compared to previous ARX input models, the OE model demonstrated superior accuracy and robustness, capturing both fast and slow thermal dynamics inherent in the cooling process. Among the tested structures, the OE (2,2,1) model achieved the best performance, with R^2 = 0.9923 and RMSE = 0.0600, indicating an excellent fit between predicted and simulated temperature profiles.

The originality of this work lies in applying a higher-order OE model to represent the transient characteristics of milk cooling and linking the model structure to physical heat-transfer behaviour. This contributes to improved system identification for process control and energy optimisation in small-scale dairy operations. Nevertheless, the study has several limitations: validation was performed using simulated data from a single facility under controlled conditions, and the model's sensitivity to measurement noise and broader operational variability was not yet explored.

Future research should integrate the OE model with advanced control strategies, such as MPC, or adaptive control, to enable real-time optimisation of milk refrigeration. Extending this modelling approach to other temperature-sensitive food processes could further enhance its industrial relevance.

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This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT
The authors state no conflict of interest.

DATA AVAILABILITY
The data that support the findings of this study are available from the corresponding author, R. Agustriyanto, upon reasonable request.

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