

Integrating Fluid Dynamics: Leveraging Simscape for Modelling and Real-Time Control of Continuous Flow Ohmic Heater

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Integrating fluid dynamics: leveraging Simscape for modelling and real-time control of continuous flow ohmic heater

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Dr. Hongwei Zhang is a leading expert in advanced process control, sustainable food processing, and artificial intelligence applications in the food industry, currently serving as the Co-Director (Academic) of the Advanced Food Innovation Centre (AFIC) at Sheffield Hallam University. He holds dual PhDs in Aerospace Engineering and Control Engineering and has over 60 peer-reviewed publications, with extensive experience in supervising PhD students and leading major research projects.

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ABSTRACT

Ohmic heating (OH) is an innovative thermal processing technology known for its rapid and uniform heating capabilities. It presents several challenges due to its complex multi-physics nature, involving electrical, thermal, and fluid dynamics phenomena. The nonlinearity of OH systems, influenced by variations in electrical conductivity and temperature, makes physical modelling a necessity to capture these dynamics accurately. To address this, we developed a MATLAB model using the Simscape toolbox, designed to investigate the effects of OH technology under various physical conditions of food products. This model was validated against both an established mathematical model and a pilot scale continuous flow ohmic heater (CFOH), achieving a normalised mean square error (NRMSE) of ± 0.005 and a mean absolute percentage error (MAPE) of $\pm 5\%$. It effectively simulates temperature variations in response to changes in the thermophysical properties of food, facilitating real-time system dynamics evaluations. Additionally, the model explores significant factors such as electrical conductivity, product temperature, density, flow rate, and electric field strength. The successful application of this physical model underscores its potential in designing model-based control systems to enhance the efficiency and performance of the CFOH processes.

Keywords: continuous flow ohmic heating; Simscape based physical model; model validation; advanced process control; energy efficiency

1. Introduction

Heating is a critical step in various food processing applications, serving essential purposes, including pasteurisation, sterilisation, cooking, and pre-treatment for microbiological safety and enhanced shelf-life [1], [2]. These commercial food processing procedures are frequently conducted using conventional heating methods. Traditional heating processes involve fuel burning, primarily through the combustion of coal, oil, or natural gas. Consequently, burning of fossil fuels corresponds to

approximately 10 - 12 tons of carbon emissions annually in the United Kingdom and EU member states [3]. Additionally, the heat transfer rates from an external medium to the food material and factors like the material's thermal conductivity limit the efficiency of conventional heating procedures [4]. This leads to over-processing, which results in undesired temperature peaks and poor product quality [5]. Hence, conventional heating methods are neither environmentally friendly nor energy efficient as they depend on slow, surface-to-centre heat transmission mechanism.

Owing to these problems, volumetric heating technologies have gained attention for food processing systems [6]. Ohmic heating (OH) is one of these methods, which is based on moderate electric field (MEF) that involves application of electric field $\leq 1\text{kV/cm}$ to the food material. It is a unique and efficient method in which electric current is passed directly through a food product causing its resistance to convert electrical energy into thermal energy [7]. As a result, volumetric and uniform heating effect is produced that leads to high energy efficiency and reduced cooking time. Hence, this technology has immense potential for industrial applications.

Nevertheless, due to variations in electrical conductivity, non-homogeneous combinations are challenging to heat uniformly [8]. To improve heat dispersion, such mixtures may need intermittent heating, stirring, or a combination of power sources [9]. This might cause the materials to be over-heated or under-heated, which would yield unfavourable results on an industrial scale [10].

Therefore, for the successful application of OH technology in food processing, an understanding of the regulatory parameters governing this process is essential. This involves adherence to the applied electric field, temperature, time, and other variables necessary to achieve desired food safety outcomes while preserving product quality. However, prior to implementing OH in real-time systems with food materials, conducting simulations and modelling is a prudent approach. This allows to gain insights into how the system behaves under different conditions and variations in process variables.

Several studies have been conducted to enhance potential control mechanisms with substantial advancements in mathematical models and subsequent control technologies. Various mathematical models of the OH process for a range of food products have been developed and validated. However, these models vary in their underlying assumptions and solving methods for equations. For instance, Guo et al. [11] explained that the use of Laplace equation model calculates voltage drop and minimises

simulation computation time. Nevertheless, it is less effective at processing distortions of the electric field caused by variations in electrical conductivity in food material. Similarly, Engchuan et al. [12] implemented the finite difference model to estimate temperature at specified nodes in meatballs and indicated that Skuprasert's model (semi-empirical) showed the highest accuracy with ohmic heated meatballs.

Moreover, Benabderrahmane and Pain [13] developed a slip phase model for solid/liquid mixture in ohmic heating sterilization. All physical properties for both phases (solid and liquid) in the mixture were assumed to be constant and homogeneous throughout the process. Similarly, Zaror et al. [14] established a mathematical model based on unsteady-state energy balances in solid/liquid phases. They identified that the heat generation rate is unstable within the mixture depending on the kinetics of the processing material. However, the general energy transfer equations of the OH system which consist of the thermal conduction and internal energy generation equations, serve as the foundation of each mathematical model [15]. These mathematical equations are either converted to block diagrams for system behaviour analysis or linearized to a transfer function to get system response. While such models can be highly accurate for well-understood systems, they may not fully capture the intricacies and real-time dynamics of complex systems [16]. As a result, physical modelling has emerged and has ignited a broad industry revolution [17], [18].

Physical models are often more realistic representations of real-time systems because they can accurately replicate the actual behaviour of the system. They can capture complex, nonlinear, and dynamic behaviours that may be challenging to represent accurately with mathematical equations alone [19], [20]. Physical models can also integrate real-time sensor data from real-time systems, allowing for continuous monitoring and adjustment. This capability enables them to be paired with control systems and optimisation algorithms to offer real-time control and adaptive decision-making based on sensor data, making physical models particularly valuable for predictive maintenance, monitoring, and control applications [21].

Furthermore, studies have been conducted on botanical drinks, fruit juices, dairy products, and meats to observe the influence of process control parameters on temperature, structural variations, and microbial inactivation times using mathematical models of static/ batch ohmic heating systems. However, according to the best of writer's knowledge, a continuous flow ohmic heater has not yet been modelled as a physical

system, which can prove to be a valuable tool in thoroughly studying system behaviour from a control engineering perspective. The physical model can also simulate various scenarios to assess system behaviour under varying physical and thermal properties of the product under process. This flexibility is valuable for optimization, risk assessment, and scenario planning.

Hence, this research presents the physical modelling of the continuous flow ohmic heating system. The model has been developed in the Simscape library of MATLAB 2023a. The simulation results have been validated against a developed mathematical model by [Oluwole-Ojo et al. \[22\]](#) and a real-time pilot-scale continuous flow OH system using saline solution and orange juice. Further, a PID controller has been integrated with the physical model for optimized energy consumption and analysis.

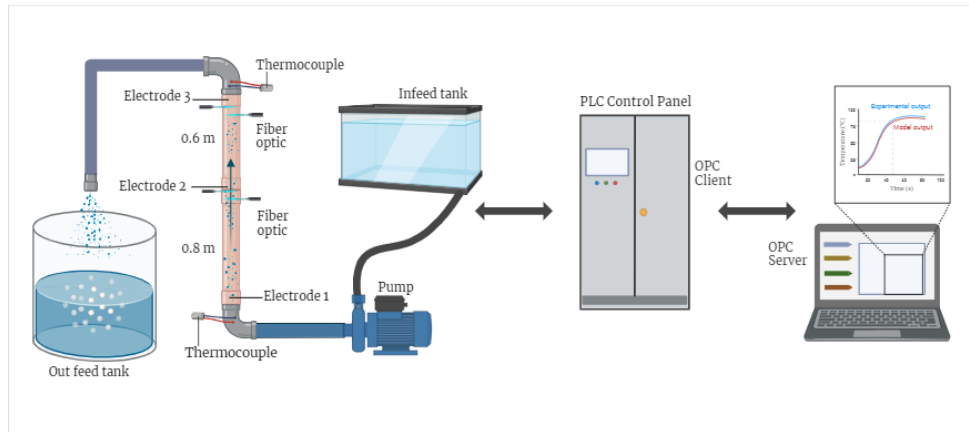
2. Design of pilot scale ohmic heating system

The continuous flow Ohmic Heating (OH) system installed in the laboratory is a pilot-scale plant that operates at voltages up to 4.2 kV and delivers a nominal power of 10 kW with materials of electrical conductivity range 0.11–1.1 S/m. The system comprises in-feed/out-feed tanks, a flow rate control pump, an applicator, and PC-based Human Machine Interface (HMI) for its standalone operation.

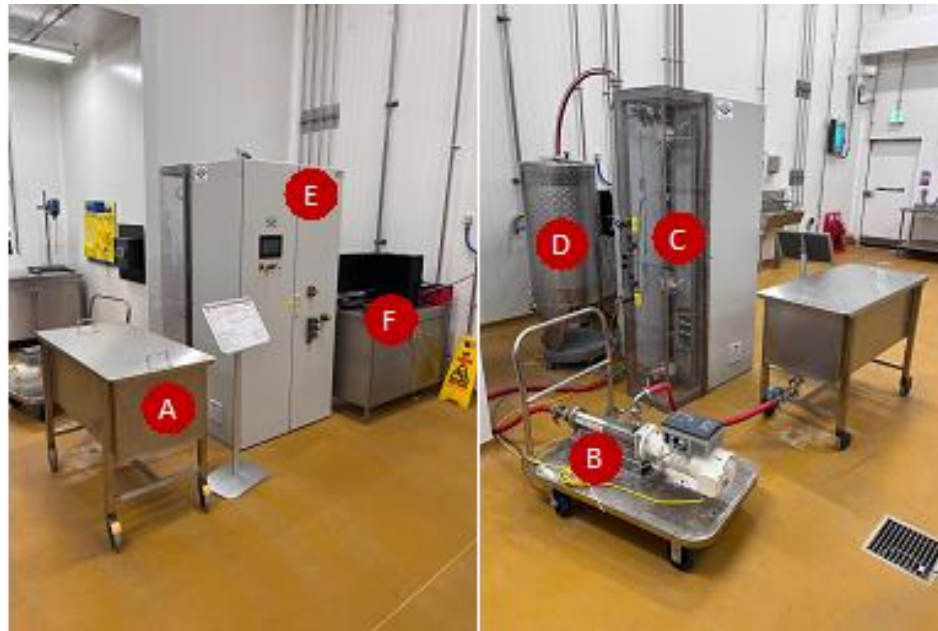
The applicator is a critical component responsible for delivering electrical energy to the material. It features a parallel arrangement of three proprietary coated Titanium electrodes, 0.8 m, and 0.6 m apart, respectively, as shown in figure 1 (a). This arrangement forms two separate heating sections when a high voltage is supplied to the central electrode (electrode 2 as labelled in figure 1 (a)) relative to the infeed (electrode 1) and outfeed (electrode 3) electrodes. One section is created 0.8 metres between the infeed and centre electrodes (1 and 2), while the other is 0.6 metres between the central and outfeed electrodes (2 and 3).

The dimensions of the applicator bore are 20 mm with 1.4 m length that provides a significant volume of 439600 mm³. Liquids and soft particulate materials can easily be pumped through the chamber bore. Additionally, the applicator chamber incorporates a network of temperature sensors, including fibre optic probes and thermocouples, strategically placed at the infeed, centre, and outfeed of the ohmic heater. These sensors play a pivotal role in temperature data collection, ensuring the safety, efficiency, and consistency of the heating process.

The voltage and power for the electrodes can be controlled through a user-friendly PLC-based HMI. However, the system can also be driven and controlled by PC based platform that was developed by [Oluwale-Ojo et al. \[23\]](#) in MATLAB Simulink (version 2022b). The control platform communicates via an Open Platform Communications (OPC) server, facilitating the collection of temperature data used for closed-loop feedback control of the thyristor voltage in the real-time Ohmic Heating system. This enhances the capabilities of the OH system, enabling precise control, real-time data analysis, and improved monitoring.



(a) Schematic diagram of Continuous Flow Ohmic Heater setup.



(b) (A): Infeed tank; (B): Pump; (C): Heating chamber and electrodes; (D): Outfeed tank; (E): PLC Control Panel; (F): PC-based control system.

Figure 1. Schematic model (a) and installed Continuous Flow Ohmic Heater in Advanced Food Innovation Centre (b).

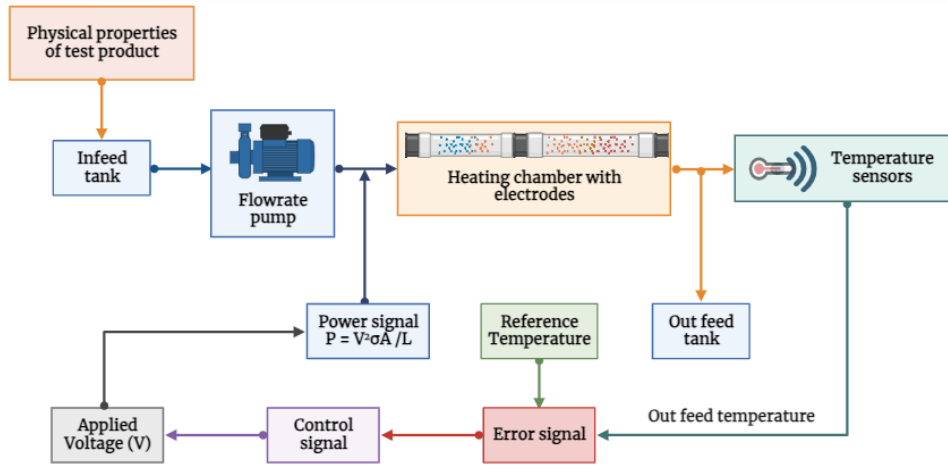


Figure 2. Block diagram representation of the developed model in MATLAB/Simscape.

3. Methodology: Physical modelling of ohmic heater using Simscape

The physical model of the ohmic heater was developed using MATLAB 2023a in the Simscape library. Figure 2 illustrates a block diagram representing the process of this model. It explains that the physical properties of the food product sample are designated as input parameters for the infeed tank. Simultaneously, power signal and thermal lag are computed providing electrical energy to the ohmic heating chamber. Within the chamber, electrical energy is converted to the thermal energy as the food sample is pumped in. A temperature sensor is integrated into the model to record temperature. After the model development, temperature sensor data has been used to validate the model. Further, a PID controller has been deployed where error signal is estimated from the output temperature and reference temperature.

This section provides step-by-step details of developing the physical model which is used to accurately simulate the functioning and operations of the real-time ohmic heating system. Figure 3 illustrates a flow chart of the procedure followed.

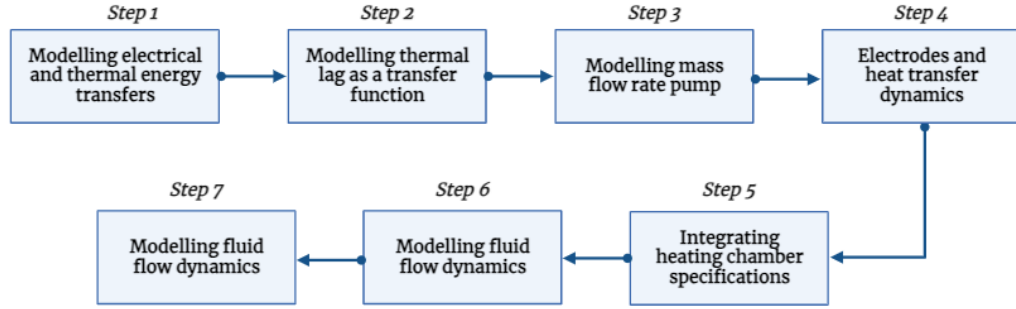


Figure 3. Flow chart of the developed model in MATLAB/Simscape.

3.1. Step 1: Thermal energy transfer system

The technology of ohmic heating (OH) is based on the passage of electric current through materials for heating purposes [24], [25]. This concept is fundamentally governed by Ohm's law, in which food products behave as resistors (inverse of electrical conductivity) that are heated due to the dissipation of electrical energy in an OH chamber [26].

Heat is generated within the conductor (food material) in proportion to its conductivity and the square of the applied electric field strength. Consequently, the ohmic heating process can be deconstructed into two basic sub-processes: the externally applied electrical energy or power, and internally generated thermal energy. The electrical power relies on an applied voltage between the electrodes, which results in the formation of electric field. This field causes a flow of current that leads to the production of heat due to the inherent resistance of the material. The thermal energy generated through this phenomenon contributes to the overall temperature rise of the product. Therefore, both these processes are inextricably linked. This is expressed by equation 1, where Q is the internally generated volumetric heat (W/m^3) as a result of the application of an electric field E to the food material with a given electrical conductivity σ (S/m).

$$Q = \sigma |\nabla E|^2 \quad (1)$$

The main objective of OH technology is to raise the temperature of a food product for pasteurisation, sterilisation, or cooking applications. Hence, the governing equations of electrical and thermal energy transfers are mathematically represented as described by [27] in equation 2. Here, T is the temperature, ρ is the density, c is the specific heat capacity, and k is the thermal conductivity of the material under process. Furthermore,

the derivative terms, $\nabla \cdot (k \nabla T)$, $\rho \nabla \cdot v$, and $\nabla \cdot q_r$ represent heat transmitted through the fluid by conduction, work done by the fluid, and radiative heat transfers, respectively.

$$\rho c \frac{\partial T}{\partial t} = \nabla \cdot (k \nabla T) + Q - \rho \nabla \cdot v - \nabla \cdot q_r \quad (2)$$

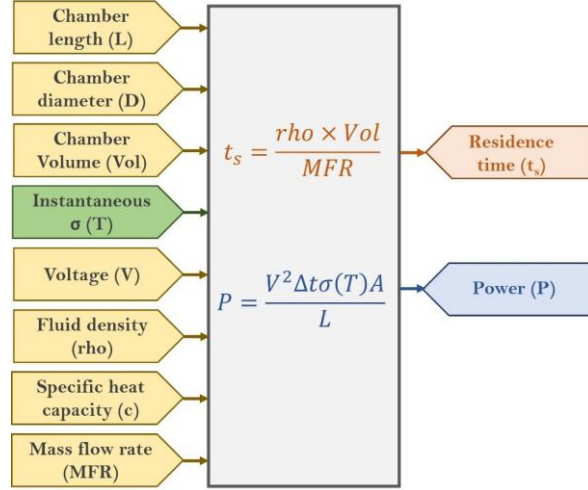


Figure 4. Schematic layout of power signal model subsystem.

As a result of heating food materials, the electrical conductivity increases linearly as a function of temperature. Equation 3 describes this relationship with ΔT known to be the change in temperature.

$$\sigma(T) = \sigma(1 + k \Delta T) \quad (3)$$

These dynamic variables are crucial for quantifying the input power to the system. They reflect the mathematical interplay between geometry, material physical properties, temperature variations, and voltage. Therefore, these parameters are integrated in the equation 4 and modelled in the developed OH system for power transfers, where Δt represents the temperature change rate $\frac{\Delta T}{\Delta t}$. Considering the parallel plate configuration of the electrodes in the developed model, A is the cross-sectional area, and L is the separation between the electrodes. Figure 4 shows the model of the subsystem block for input power signal.

$$P = V^2 \Delta t \sigma(T) \cdot \frac{A}{L} \quad (4)$$

3.2. Step 2: Thermal lag in the ohmic heating system

Modelling of thermal lag is essential in the physical model of the ohmic heater to accurately simulate the system's response towards variations in input power or other parameters. Thermal lag describes the time-dependent response of the material when its temperature changes, accounting for the time needed for heat to propagate through the material. This is modelled by calculating the characteristic time τ for heat to propagate through the material, taking into account the residence time (t_s) of the fluid inside the heating chamber.

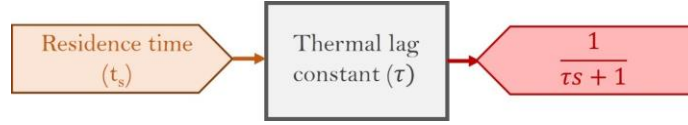


Figure 5. Subsystem model of thermal lag.

Residence time is determined with key parameters like density, thermal conductivity and diffusivity, geometry, and mass flow rate of the test material. The estimated τ has been incorporated in the physical model by introducing a first-order transfer function representing heat transfer lag, as shown in equation 5. Subsystem block of thermal lag is displayed in figure 5.

$$G(s) = \frac{1}{\tau s + 1} \quad (5)$$

3.3. Step 3: Mass flow rate pump

The flow rate pump is a representation of mechanical pump in the ohmic heating system. This source can maintain a defined mass flow rate irrespective of pressure variations. This quantity is kept constant as 0.0167 kg/s (1 L/min) for simulations. The volumetric flow rate ($\dot{Vol}$), input density (ρ_i) and output density (ρ_o) of the material, and mass flow rate ($\dot{m}$) throughout the system are related as follows in equation 6:

$$\dot{m} = \begin{cases} \rho_o \dot{Vol} & \text{for } Vol \geq 0 \\ \rho_i \dot{Vol} & \text{for } Vol < 0 \end{cases} \quad (6)$$

3.4. Step 4: Electrodes and heat transfer dynamics

In the Simscape simulation, we incorporated a regulated conductive heating element to emulate the conductive heating process induced by the voltage applied across the electrodes. This heating element serves as a model for the conductive heating of the electrodes, driven by controlled input power and the integrated thermal lag signal. The

geometry of the heating electrodes' walls is defined as cylindrical. Heat conduction (Q_{ch}) across the wall of the cylindrical heating chamber is estimated using equation 7, where k is the thermal conductivity of the electrode material, L is the length of heating chamber, d_o and d_i are the outer and inner diameters of the electrodes, while T_{d_o} and T_{d_i} are the respective temperatures at the outside and inside of the electrodes:

$$Q_{ch} = 2\pi k \frac{L}{\ln\left(\frac{d_o}{d_i}\right)} (T_{d_o} - T_{d_i}) \quad (7)$$

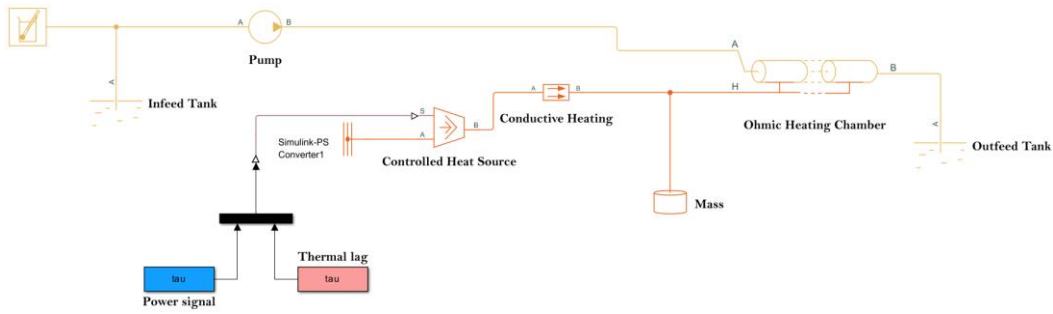


Figure 6. Ohmic heating subsystem in the physical model.

3.5. Step 5: Fluid flow dynamic modelling with heating chamber specifications

A heating pipe component has been introduced to replicate the fluid flow dynamics of the heated liquid food material within the heating chamber. This component incorporates the essential physical properties of both the flowing substance and the heating chamber. The heating chamber walls are defined as rigid and devoid of thermal expansion. The chamber wall is assumed to be adiabatic with laminar flow of the food material, ensuring thermal conduction over thermal convection. Temperature difference and mass flow rate between the inlet and outlet of the heating chamber are initially nominal. The interaction between the conductive heat element and the heating pipe mimics the gradual temperature increase of the flowing fluid through the system.

Additional specifications, including fluid density, inertia, mass flow rate, and nominal pressure in the system, are also tailored to the characteristics of the product undergoing processing in the ohmic heating system. Figure 6 displays the modelling subsystem of conductive heating process and ohmic heating chamber.

3.6. Step 6: Temperature sensing model for feedback loop

The physical model incorporates virtual temperature sensors to replicate the behaviour of fibre optic probes and thermocouples found in the actual pilot plant Ohmic Heater. Operating concurrently with their physical counterparts, these virtual sensors collect temperature data, recreating the complete heating profile of the substance within the physical model.

The temperature sensor block functions as an ideal sensor measuring absolute temperature within a thermal liquid network at the outlet of the heating chamber. No mass or energy flow occurs through the sensor. The data collected from both virtual and physical temperature sensors is utilised to validate the simulated temperature profiles of the developed model.

4. Experimentation and model validation

The designed physical model has been validated against the mathematical model by [22], as well as against the real-time data from pilot-scale Ohmic Heater (OH). Initially, open-loop testing was performed to observe the system's response to variable voltage, conducted without the influence of feedback control mechanisms. The input voltage, electrical conductivity (EC), and mass flow rate (MFR) of the product were varied in simulation to record the corresponding output temperature of the model.

Secondly, similar variations were made in the OH system to compare the response of the model and real-time system. Experimental data were collected by performing different experiments using the continuous flow ohmic heater on samples of saline solution ($\sigma = 0.2 - 0.9 \text{ S/m}$) and orange juice ($\sigma = 0.24 \text{ S/m}$). Outputs of these models and the OH system were evaluated in terms of normalised root mean square error (NRMSE) and mean absolute percentage error (MAPE) for each simulation time. Numerical results for these experiments are displayed in Table 1.

Following the open-loop validation, a PID controller was implemented in the physical model and later in the real-time system with both sample products – saline solution and orange juice. Analysis of the behaviour of the physical and real-time system with a controller was performed in terms of the overall performance, rise time, maintaining the desired temperature set-point, and energy consumption.

4.1. Experimental setup

Experiments were conducted to record the behaviour of the Ohmic Heater corresponding to varying conditions. For the setup of experiments, it is essential to remove impurities from the equipment. Therefore, water was initially run through the in-feed and out-feed tanks, as well as the heating chamber, for cleaning and preparation purposes.

Table 1. Temperature and errors with varying parameters.

	Parameters/ Outputs	Voltage (V)		Electrical conductivity (S/m)		Mass flow rate (kg/s)	
		2000	2800	0.2	0.9	0.008	0.075
Temperature (°C)	<i>Mathematical</i>	48.07	89.80	32.94	94.00	76.94	24.68
	<i>Physical</i>	48.12	89.45	33.29	94.11	76.97	24.68
Errors	<i>NRMSE</i>	0.0039	0.0025	0.0062	0.0046	0.0028	0.0046
	<i>MAPE (%)</i>	2.82	3.27	3.07	4.37	3.59	1.26

Next, saline solution was prepared while precisely measuring the electrical conductivity of the solution using a conductivity meter. It is crucial to measure the electrical conductivity of this solution accurately, as this parameter plays a significant role in the ohmic heating process. Saline solutions of different conductivity, ranging from 0.2 to 0.9 S/m were prepared for testing. Simultaneously, the initial temperature of each saline solution sample was measured and recorded. This initial temperature served as the starting point for the experiment. Preparation for experiments with 100% concentrated orange juice was made in a similar manner.

The following steps include setting the initial and target conditions for the experiments. A self-developed user interface was used to input all control parameters such as voltage, target temperature, mass flow rate and other physical properties of the sample.

After running the experiment, data including temperature and all other relevant parameters, were collected, and saved into the system via OPC communication. The temperature data collected from the experiment were then compared with simulation data. This step involves assessing the accuracy and robustness of the physical model by comparing real system's behaviour with simulations.

4.2. Model validation

For validating the physical model, open-loop outputs of the mathematical model were compared with those of the physical model. The comparison involved varying the input voltage, initial electrical conductivity, and mass flow rate to assess the performance of both the models.

4.2.1. Varying input voltage

Step voltage values of 2000 V and 2800 V were evaluated for model validation of physical against the mathematical model. Other conditions, such as mass flow rate (0.0167 kg/s) and electrical conductivity (0.35 S/m) were maintained constant throughout the runtime. Initial temperature of the product (saline solution) was 20 °C. It was observed that increasing the applied voltage from 2000 V to 2800 V resulted in a higher final temperature, reaching 48.05 °C and 89.79 °C, respectively. However, this increase exhibited nonlinear behaviour. The temperature gradient indicating the rate of temperature increase was steeper for the 2800 V compared to 2000 V. This suggests that higher input voltages induce a more rapid temperature rise due to the greater current flow at higher voltage values. The increased current flow enhances electrical conductivity as the temperature of the solution rises, leading to both a higher final temperature and a steeper temperature gradient.

Figure 7 shows the outputs of the open-loop physical model and the mathematical model. The rise time for both models is comparable, with observed values of 100 seconds for 2000 V and 150 seconds for the 2800 V. This difference in rise time is viewed insignificant given that the temperature gradient is considerably higher for 2800 V compared to 2000 V. However, an offset of 5 °C – 7 °C exists between the temperature gradients of the mathematical and physical models, although both models achieve the same final temperature achieved at any supplied voltage. The physical model exhibits a slower response compared to the mathematical model. This discrepancy is attributed to the thermal lag incorporated into the physical model, which more accurately represents the real-time ohmic heating unit. In contrast, the mathematical model assumes no energy losses and no system delays, leading to a more idealized and faster response.

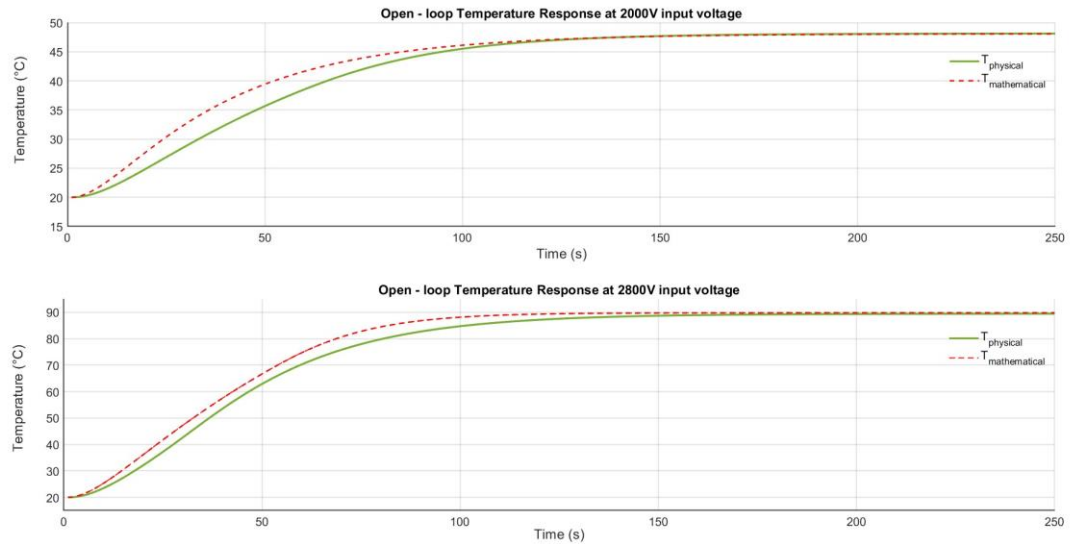


Figure 7. Model response with 2000 V and 2800 V input voltage to the physical system.

4.2.2. Varying electrical conductivity (EC)

Similarly, the electrical conductivity of the saline solution was varied between 0.2 S/m and 0.9 S/m to evaluate against constant supply voltage of 2000 V and mass flow rate 0.0167 kg/s (1 Liter/min). It was observed that the electrical conductivity of the saline solution significantly influences the final temperature. Specifically, higher electrical conductivity (0.9 S/m) resulted in a higher final temperature (94.11 °C), while lower electrical conductivity (0.2 S/m) led to a lower final temperature (33.29 °C) within the same time interval. It can also be manifested that changes in electrical conductivity do not produce a proportional change in temperature. This highlights the relationship between electrical conductivity, temperature, and current flow rates in the solution. Higher electrical conductivity facilitates a greater flow of current, leading to higher temperature.

Figure 8 illustrates the behaviour of models with varying electrical conductivity (EC) under a step input voltage of 2000 V. Both models reach a similar final temperature and exhibit a rise time of 140 seconds, suggesting that the rise time is primarily influenced by the voltage parameter. However, despite achieving the same final temperature, the models display different temperature gradients depending on their conductivity. Specifically, the model with an EC of 0.9 S/m shows a significantly higher rate of temperature change. During the rise time, there is a notable temperature difference ranging from 3 °C to 10 °C between the two models. This discrepancy increases with higher electrical conductivity and can be attributed to the consideration of I^2R energy

losses caused by the increased current density associated with higher conductivity in the physical model.

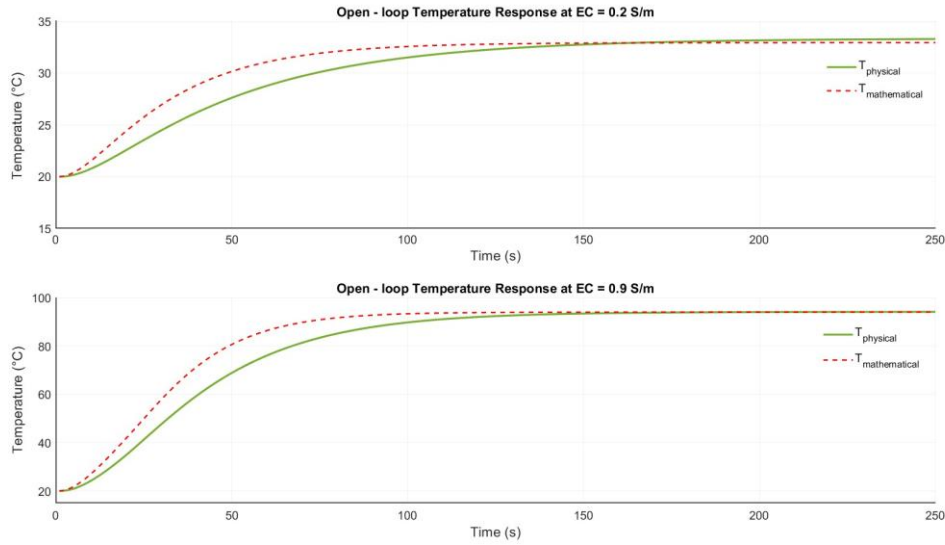


Figure 8. Model response with 0.2 S/m and 0.9 S/m initial electrical conductivity of the product.

4.2.3. Varying mass flow rate (MFR)

Subsequently, the mass flow rate was varied to have insights into the dynamics of the system while validating the model. Hence, MFR was varied from 0.008 kg/s (0.5 Litre/min) to 0.075 kg/s (4.5 Litre/min). It can be observed that reducing the mass flow rate resulted in a higher output temperature, while increasing the mass flow rate led to a lower output temperature. This demonstrates an inverse relationship between MFR and temperature during ohmic heating. This observation attributes to the phenomenon of temperature build-up inside the heating chamber and the product. Slower flow of particles allows for more extended contact time with the electrodes, leading to higher temperature build-up.

Figure 9 depicts the final temperatures achieved at different mass flow rates (0.008 kg/s and 0.075 kg/s). The data reveal that the slower-flowing product attains a higher final temperature (76.97 °C) compared to the faster-flowing product (24.68 °C). Despite the rise time being shorter at the higher mass flow rate of 0.075 kg/s, the final temperature and temperature gradient are notably lower compared to the slower mass flow rate. These findings underscore the critical importance of controlling mass flow rate (MFR) to achieve the desired temperature profile. In practical applications, adjusting the fluid flow rate through the ohmic heating system provides a means for precise temperature regulation.

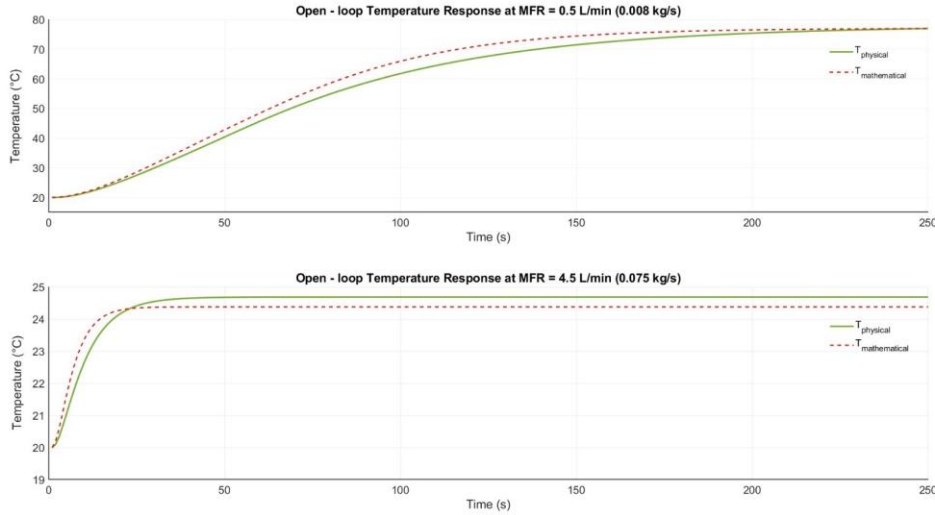


Figure 9. Model response with 0.008 kg/s and 0.075 kg/s flow rate of the product.

4.2.4. Validation against real-time data

Responses of both the mathematical and physical models were compared against the real-time data with the sample of saline solution with moderate electrical conductivity of 0.52 S/m. The input signal was an increasing voltage with large random steps ranging from 1200V to 1800V. Figure 10 show the outputs of real-time, mathematical, and physical models. It is positive to note that both the physical model and the real-time system exhibit consistent behaviour in terms of nonlinear temperature rise with increasing voltage. It can be seen from the figure that the mathematical model appears to show a lead of 3 °C from 200 s onwards, whereas the physical model closely follows the response of the real-time OH plant.

Figure 11 compares the simulated temperature outputs from both models with the real-time temperature output to observe the combined effect of low conductivity and high mass flow rate. Short voltage steps were applied at random intervals for a greater runtime to observe the performance, robustness, and behaviour of the physical OH model. During these tests open-loop validation, the flow rate was maintained at a constant 1 L/min – 0.0167 kg/s. The results demonstrate a high degree of conformity between the simulated and experimental data, maintaining alignment up to 600 s for the mathematical model and up to 900 s for the physical model. However, deviations between the models and the real-time data were observed corresponding to the increasing small step voltages. Generally, a proportionate rise in the real-time temperature response is expected, as seen in figure 10. Nevertheless, the real-time temperature seems to drop by approximately 3.5 °C

compared to the simulated response of the physical model. The reason for this divergence may be ascribed to the behaviour of the hardware temperature sensor or unaccounted nonlinearities caused by fluid backflow inside the heating chamber.

Figure 12 presents the results obtained with low conductivity and low mass flow rate of the saline solution. These different scenarios were selected to assess all combinations of control parameters for the operation of OH plant. Additionally, step input voltage was dropped at 450 s to evaluate the response of the model with voltage reduction. From 0 to 450 s, when a steady step rise in voltage was applied, the temperature responses from both the models and the real-time OH system were proportional to the applied voltage and exhibited high conformity. However, between 500 and 600 seconds, when the step voltage was reduced, a temperature difference of about 2 °C was observed between the outputs of the physical model and the OH plant. This deviation can be attributed to minor discrepancies in the temperature sensors.

Similarly, the same validation procedure was performed with orange juice of conductivity 0.24 S/m and constant mass flow rate of 0.0167 kg/s – 1 L/min. Figure 13 presents the temperature response where a small discrepancy of 2 °C for the physical model can be observed from approximately 210 s to 250 s. The reason for this deviation is unknown.

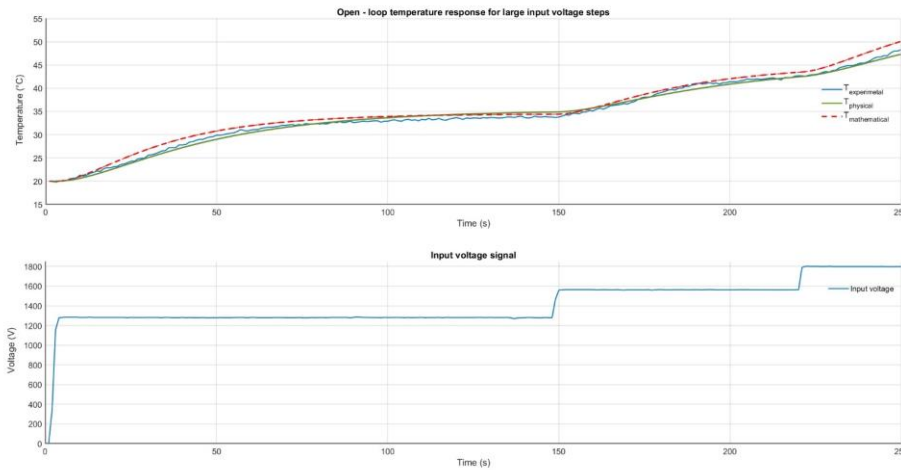


Figure 10. Physical model response with saline solution against experimental data and mathematical model at electrical conductivity = 0.52 S/m and mass flow rate = 1 L/min.

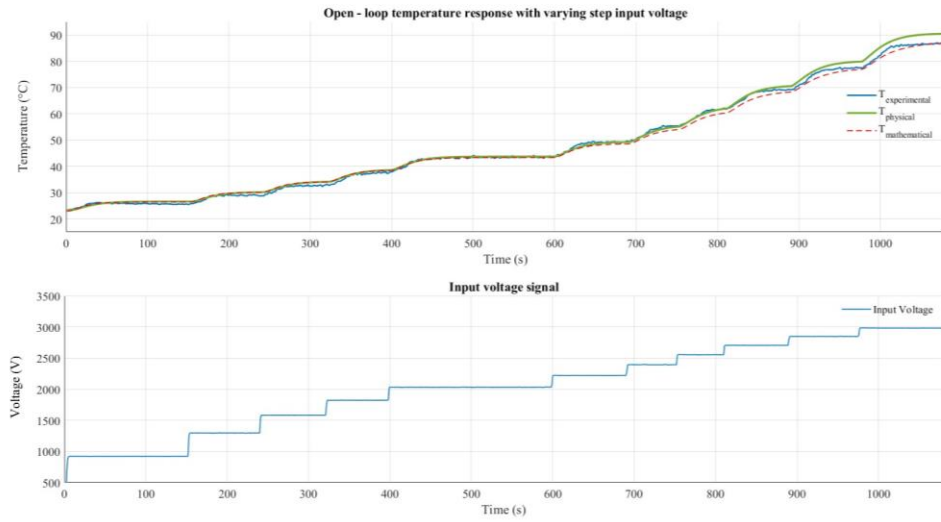


Figure 11. Physical model response with saline solution against experimental data and mathematical model at electrical conductivity = 0.3 S/m and mass flow rate = 1 L/min.

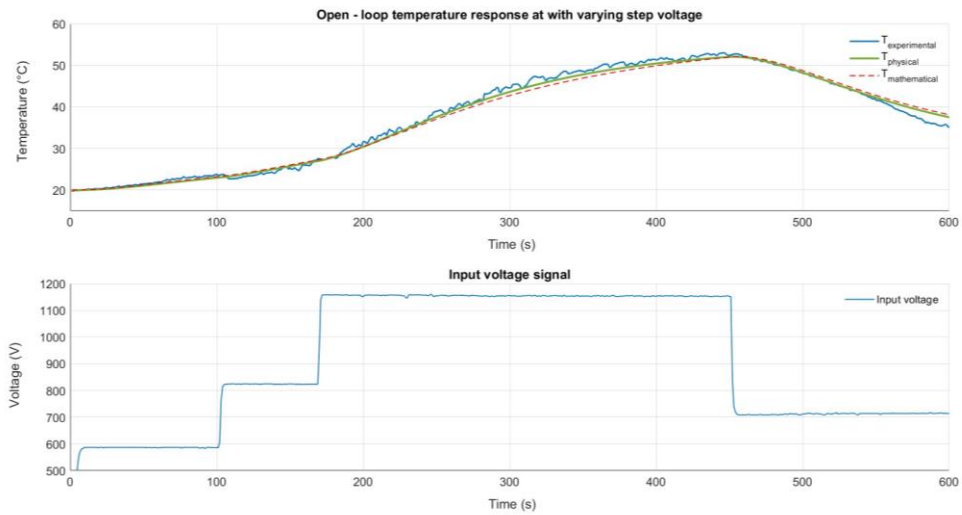


Figure 12. Physical model response with saline solution against experimental data and mathematical model at electrical conductivity = 0.3 S/m and mass flow rate = 0.22 L/min.

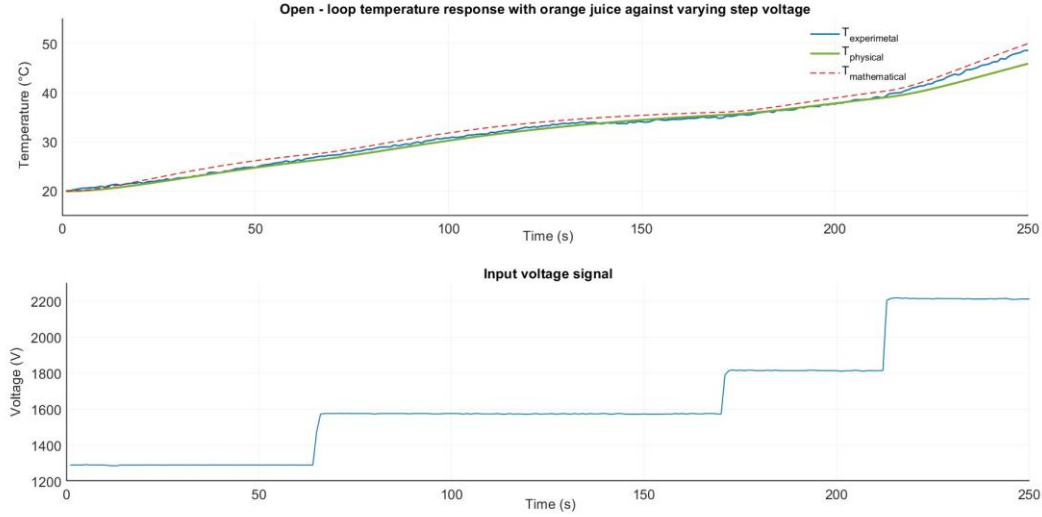


Figure 13. Physical model response with orange juice against experimental data and mathematical model.

The overall comparison of the physical model shows conformity to the OH plant with relatively low NRMSE and MAPE as compared to that of the mathematical model, as shown in Table 2. Close observations regarding the behaviour of the mathematical model and the physical model emphasize that the mathematical model behaves as the ideal system, whereas the physical model more realistically follows the transient temperature rise. This suggests that the developed physical model, implemented in Simscape, accounts for more detailed system dynamics, including the thermal lag. Hence, the low error values in the comparison between experiment and simulation results for most cases are a promising sign. They suggest that the Simscape-based physical model is performing well in replicating the real-world behaviour of the system.

Furthermore, the findings also highlight the importance of product electrical conductivity. It is evident from the results obtained from the range of low to high conductivities that the input voltage profile is relatively higher for low electrical conductivity solutions compared to that for high conductivity products to attain similar temperatures. This suggests that the electrical conductivity of the solution is a key parameter to adjust for precise temperature control in practical applications. These observations have practical implications for industrial and research applications of Ohmic Heating. Controlling electrical conductivity can be used to regulate the heating process, especially when specific temperature profiles are required.

Table 2. Temperature and errors of simulated models compared with experimental data.

OH Models	Saline solution: EC = 0.52 S/m, MFR = 1 L/min		
	Temperature (°C)	NRMSE	MAPE (%)
Experimental	48.19	–	–
Mathematical	49.19	0.0014	1.56
Physical	48.06	0.0013	1.57
Saline solution: EC = 0.3 S/m, MFR = 1 L/min			
Experimental	86.90	–	–
Mathematical	86.88	0.0164	1.92
Physical	90.47	0.0156	1.88
Saline solution: EC = 0.3 S/m, MFR = 0.22 L/min			
Experimental	35.10	–	–
Mathematical	38.13	0.0404	2.72
Physical	37.52	0.0404	1.97
Orange juice: EC = 0.24 S/m, MFR = 1 L/min			
Experimental	48.60	–	–
Mathematical	50.01	0.0021	5.02
Physical	47.23	0.0018	3.92

4.2.5. Implementation of PID Controller

The successful operation and control of an OH system relies heavily on precise temperature monitoring and control. Therefore, analysis of the behaviour of both the physical model and the real-time system with a PID controller is an important step in evaluating the overall performance and efficiency of the system. However, design of the PID controller with correct gains and operating voltage range to achieve a desired temperature setpoint is crucial as it has a significant impact on controller power, energy consumption, and on rise time. The PID controller achieves the required temperature by following the relative change and minimising the error between the system output and the setpoint. To this effect, voltage estimates were based on the previously observed behaviour of the open-loop system, where variables like EC and MFR had major influence on the system voltage requirement to attain a target temperature. Thus, operating voltage ranges for the controller have been computed by considering the affecting variables and the phenomenon of electrical energy transfers to thermal energy.

Different voltage ranges determined based on input parameters were provided to the PID controllers to study system response. The analysis of the temperature responses

and power consumption with different PID controllers provides valuable insights into the behaviour of the system and the impact of controller parameters. It is important to recognize that simulation and real-time systems can exhibit slight differences in behaviour due to factors such as solver settings and model simplifications. These differences can lead to differences of controller rise time in simulation and real-time experiment, as observed in figure 14a and 14b. The simulation rise time is 75 s whereas it is 50 s in the case of real-time system.

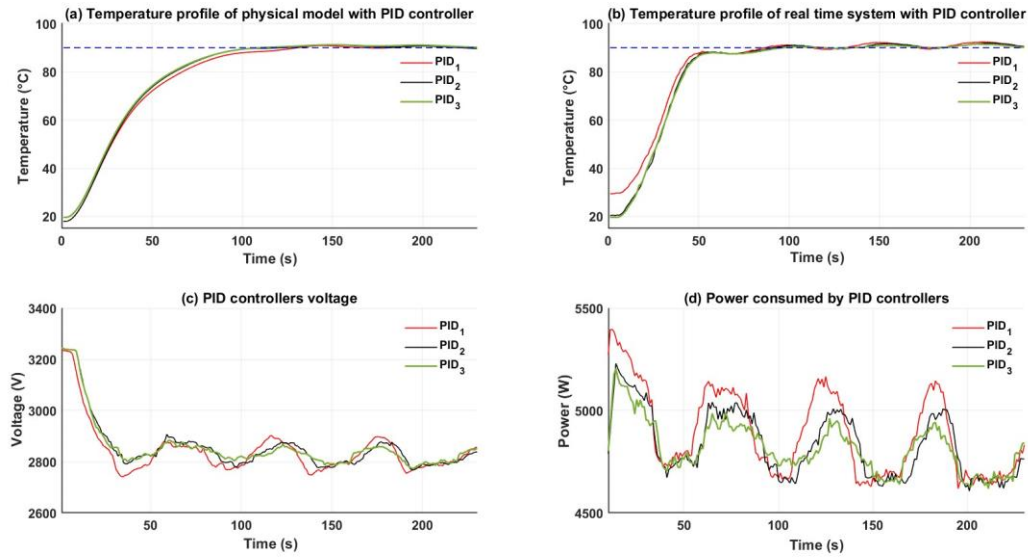


Figure 14. Physical model temperature responses with PID controllers.

Table 3. Power and energy consumption of the PID controllers against operating voltage range.

Controller	Voltage Range (V)	Average Power (W)	Average Energy (kWh)
PID ₁	2600 – 2900	4484.5	339.2
PID ₂	2800 – 2900	4817.8	334.5
PID ₃	2800 – 2850	4814	334.3

Moreover, the analysis highlights the significant role of the operating voltage window in power consumption and temperature control. The choice of operating voltage range directly affects the system's behaviour and energy efficiency. PID₁, with a wider operating voltage window, exhibits more fluctuations around the target temperature. This increased variability can lead to higher power and energy consumption as the controller makes frequent adjustments to maintain the set-point (90 °C). It was further noted that a

narrower operating window (as seen with PID₂ and PID₃ in figure 12c and 12d) can potentially improve power consumption by reducing fluctuations.

However, it is essential to strike a balance, as excessively narrow operating windows can lead to challenges in reaching the target temperature and higher rise time. The delay observed in PID₃ compared to PID₂ suggests that while a narrower operating window may reduce fluctuations, it can introduce a delay in the controller's response. This trade-off between response time and stability is a critical consideration in controller tuning.

Considering energy consumption as a performance metric, the results are displayed in table 3. While reducing the operating voltage window may save energy, it should not compromise the system's ability to maintain the desired temperature within acceptable limits.

5. Conclusion

This research presents a novel approach of Simscape based physical modelling for a real-time Ohmic Heating system. The developed model has been validated against an established mathematical model and a real-time pilot-scale Ohmic Heater. The results from the physical model are consistent with the mathematical model and with real-time system response. This shows that the validated model can effectively simulate temperature variations with the change in thermophysical properties of the food product. It also allows to evaluate system dynamics in real-time scenarios, indicating that physical models are a reliable representation of the real system responses. Model outputs provide a clear understanding of how the physical parameters and system input variables influence the overall outcomes during the Ohmic Heating process.

Moreover, a PID controller was implemented that provided a systematic approach to controlling and analysing the energy consumption behaviour of both the actual OH system and physical model design. The understanding of the voltage operating range can guide the design and control of Ohmic Heating processes, especially in scenarios where precise temperature control is required. This also enables to optimize energy efficiency, assess system performance, and make informed decisions for system improvements and control strategies. The errors observed in simulation rise time account for the solver configurations and simulation components.

Despite several improvements in the physical model design capacity to investigate the effects of significant characteristics on Ohmic Heating of food products temporal and spatial behaviour has not been studied. In future studies, validating the model's performance and temperature over time and at different spatial locations within the heating chamber shall be considered. This can help identify any discrepancies in transient or spatial behaviour. Continued research and innovation in this field will lead to improved processes and better utilisation of this technology in the food industry.

Conflict of interest statement

The authors declare no conflict of interest. The funders were not involved in any stage of this study including data collection, analyses, manuscript writing, or publishing of the results.

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Author contributions

Conceptualization, H.Z., M.A., T.B., and T.J.; methodology, T.J.; software, T.J.; validation, T.J., H.Z., M.A. and T.B.; writing - original draft preparation, T.J.; supervision, M.A., H.Z., and T.B.; project administration, H.Z., M.A., and T.B.; funding acquisition H.Z. All authors have read and agreed to the published version of the manuscript.

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