Application of Advanced Process Control to a Continuous Flow Ohmic Heater: A Case Study with Tomato Basil Sauce.

JAVED, Tasmiyah, OLUWOLE-OJO, Oluwaloba Nifemi <http://orcid.org/0000-0003-2703-1168>, HOWARTH, Martin, XU, Xu <http://orcid.org/0000-0002-9721-9054>, RASHVAND, Mahdi <http://orcid.org/0000-0002-3767-3028> and ZHANG, Hongwei <http://orcid.org/0000-0002-7718-021X>

Available from Sheffield Hallam University Research Archive (SHURA) at:

https://shura.shu.ac.uk/34271/

This document is the Published Version [VoR]

Citation:

JAVED, Tasmiyah, OLUWOLE-OJO, Oluwaloba Nifemi, HOWARTH, Martin, XU, Xu, RASHVAND, Mahdi and ZHANG, Hongwei (2024). Application of Advanced Process Control to a Continuous Flow Ohmic Heater: A Case Study with Tomato Basil Sauce. Applied Sciences, 14 (19): 8740. [Article]

Copyright and re-use policy

See http://shura.shu.ac.uk/information.html

Sheffield Hallam University Research Archive
http://shura.shu.ac.uk

applied sciences

MDPI

Article

Application of Advanced Process Control to a Continuous Flow Ohmic Heater: A Case Study with Tomato Basil Sauce

Tasmiyah Javed, Oluwaloba Oluwole-ojo, Martin Howarth, Xu Xu, Mahdi Rashvand * and Hongwei Zhang *

National Centre of Excellence for Food Engineering, Sheffield Hallam University, Howard Street, Sheffield S1 1WB, UK; t.javed@shu.ac.uk (T.J.); ojo.n.oluwole-ojo@student.shu.ac.uk (O.O.-o.)
* Correspondence: m.rashvand@shu.ac.uk (M.R.); h.zhang@shu.ac.uk (H.Z.)

Abstract: Improving the efficiency and performance of control systems in food processing remains a significant challenge for engineers and researchers. In this paper, Proportional, Integral, and Derivative (PID) control; Model Predictive Control (MPC); and Adaptive Model Predictive Control (AMPC) were implemented on a Continuous Flow Ohmic Heater (CFOH) pilot plant to process tomato basil sauce. The sauce, composed of tomato puree, basil, spices, and other ingredients, was used to assess the effectiveness of these advanced control strategies. This research presents a case study on the pilot-scale heating of tomato basil sauce, with applications in the broader food industry. The performances and energy efficiencies of the different control techniques were compared, demonstrating significant improvements in controlling the CFOH process. The results highlight the industrial practicality of using CFOH technology with advanced process controls for food processing.

Keywords: thermal processing; development; control systems; ohmic heating; tomato sauce

1. Introduction

Ohmic heating (OH) involves the direct application of electric current to food products, where electrical energy is converted into heat within the product itself, similar to the behavior of a resistor. This process achieves high thermal efficiency by eliminating the conventional heat transfer mechanisms, such as conduction or radiation, from external sources to the food [1,2]. The advantages of OH compared to conventional heating include faster heating, higher energy efficiency, unlimited heating depth, and volumetric heating [3–5]. The fundamental structure for OH system consists of at least two electrodes to pass current to the food medium. The OH can be designed as a batch system or a continuous flow system. In the batch OH system, a fixed quantity of food remains in continuous contact with the electrodes throughout the heating process. In contrast, the Continuous Flow Ohmic Heater (CFOH) allows food products to flow through a heating chamber where the electrodes are installed, facilitating continuous heating. For industrial applications that require long holding times during processes like cooking and evaporation, the batch OH system is typically employed. A notable drawback of the batch OH system is the occurrence of uneven heating in the absence of a mixing mechanism. This uneven heating is termed thermal stratification [1]. However, the CFOH offers broader potential for industrial applications compared to batch and conventional heating systems, primarily due to its improved processing speed. In addition, the continuous flow design minimizes the contact time between the food product and the electrodes, reducing the risk of fouling. This, combined with the uniform heat distribution achieved through ohmic heating, ensures that food quality is better preserved. The reduced processing time further contributes to minimizing thermal damage, making CFOH an efficient and quality-focused heating solution for industrial food processing [6]. Furthermore, CFOH systems offer the potential for industrial scalability while maintaining precise control over both temperature and residence time, which is crucial for meeting the specific requirements of different food

check for updates

Citation: Javed, T.; Oluwole-ojo, O.; Howarth, M.; Xu, X.; Rashvand, M.; Zhang, H. Application of Advanced Process Control to a Continuous Flow Ohmic Heater: A Case Study with Tomato Basil Sauce. *Appl. Sci.* **2024**, *14*, 8740. https://doi.org/10.3390/app14198740

Received: 26 August 2024
Revised: 23 September 2024
Accepted: 25 September 2024
Published: 27 September 2024

Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

products. This ensures consistent product quality and enhances energy efficiency, making CFOH systems an ideal solution for large-scale food processing applications [7].

The general design of the CFOH includes an infeed pump to transport the food and holding tubes to attain the desired lethality, which adds to the complexity of the system. Various configurations, like parallel plate, co-axial, multi-point, and perforated electrodes, have been deployed for batch and continuous flow OH systems. The electrode material is also carefully selected to be highly conductive and corrosion-resistant, as well as compatible with the food product, to prevent any chemical reactions during the heating process that could compromise food safety and quality [1–5,8,9].

Foods with a high content of water and ionic salts, whether in homogeneous or heterogeneous form, are ideal for OH applications [1]. OH is utilized in various industrial processes, such as preheating [10], cooking [11], extraction [5,6,12], sterilization [13,14], and pasteurization [15–17], where precise temperature control is essential to achieve effective microbial lethality while maintaining food quality. Additionally, energy efficiency in these processes is a growing concern, prompting industries to evaluate and optimize their control systems.

The Proportional–Integral–Derivative (PID) controller is the most widely used traditional control method in these systems. However, due to its single-input nature, PID control often struggles to meet the increasingly stringent requirements for modern heating processes. It tends to provide limited temperature control precision and lacks built-in energy-saving features, making it less suitable for advanced applications that demand both high accuracy and optimized energy consumption [18,19]. This highlights the need for more intelligent control strategies in the food processing industry.

In response to the limitations of traditional control methods, studies have introduced advanced algorithms, such as artificial neural networks, and neuro-fuzzy systems to improve the energy efficiency and thermal comfort of centralized heating systems [20–22]. These algorithms have yielded continuous advancements in system performance. However, there is an inherent challenge in balancing the conflicting objectives of maximizing thermal comfort and minimizing energy consumption and computational demands. A promising solution to this challenge is Model Predictive Control (MPC), which uses predictive models to optimize control over a set time horizon, thereby minimizing cost functions. Unlike traditional controllers that target a single objective, MPC allows for a more flexible control by addressing multiple control goals simultaneously within an optimization framework [23]. Additionally, MPC offers significant potential for reducing energy consumption and greenhouse gas emissions while enhancing thermal comfort [24].

However, a traditional MPC system is designed around a nominal operating point, where the control model is valid, often relying on a linearized version of a nonlinear system to approximate a linear time-invariant (LTI) model. In contrast, Adaptive Model Predictive Control (AMPC) continuously updates the operating points of the system based on real-time data. This dynamic adjustment ensures that the control model accurately reflects the changing conditions of the system, maintaining consistency and improving control performance over time [25].

These controllers show significant potential for application in industrial processes. However, gaps remain in the literature regarding the energy efficiency of CFOH systems at the pilot-plant level and the feasibility of implementing advanced process control in such settings. This paper aims to address these gaps by analyzing the performance of the traditional Proportional–Integral–Derivative (PID) control, Model Predictive Control (MPC), and Adaptive Model Predictive Control (AMPC) in the processing of tomato basil sauce using a CFOH pilot plant.

2. Materials and Methods

2.1. Sample Preparation

A total of 50 L of tomato sauce was prepared from commercially available pure tomato puree purchased from a local market (Figure 1a), which was then mixed with basil, spices, olive oil, and other ingredients (Figure 1b). The proportion of oil to other ingredients was approximately 4% of the total volume.

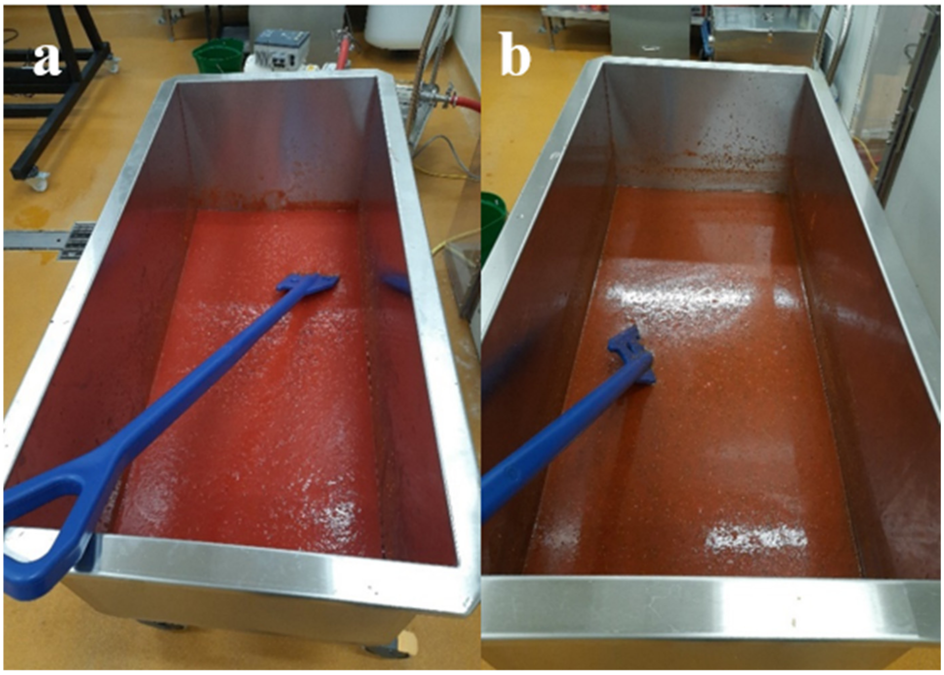

Figure 1. (**a**) Pure tomato puree before the addition of spices and ingredients. (**b**) The tomato basil sauce is prepared after the addition of spices and other ingredients.

2.2. Heating Process

The tomato basil sauce was processed using the Continuous Flow Ohmic Heater (CFOH). Prior to heating, the sauce underwent initial mixing in the infeed tank to ensure homogeneity. Continuous paddling was maintained throughout the process to ensure uniform composition during heating. The CFOH heating chamber for processing the sauce is shown below in Figure 2.

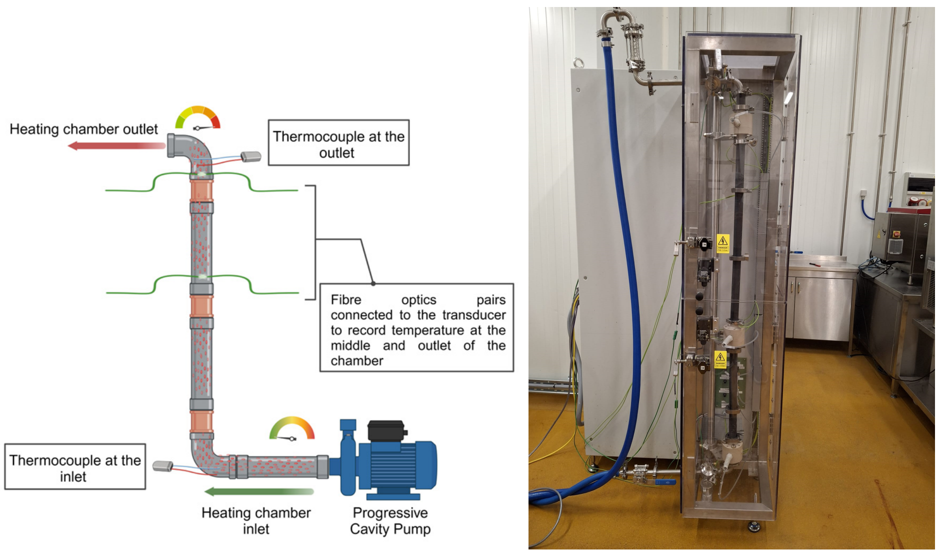

Figure 2. Heating chamber with three electrodes in the CFOH system pilot plant at NCEFE.

The Continuous Flow Ohmic Heating (CFOH) system comprises components, including a computer, infeed and outfeed tanks, a heating chamber with three colinearly arranged electrodes, thermocouples, fiber optic temperature sensors, and a control panel. The system operates at a high voltage (HV) range from 0 to 4.2 kV and a maximum power output of 10 kW. High voltage is applied to the central electrode, positioned between the infeed (electrode 1) and outfeed (electrode 3) electrodes, creating two distinct heating sections: one between the infeed and central electrode, and another between the central and outfeed electrode. Figure 2 illustrates the configuration of the applicators/electrodes and the applicator housing, which are connected to the outfeed tank at the top and the infeed tank via a pump at the bottom.

The system features a human–machine interface (HMI) for manual control and is also linked to a personal computer (PC) for automated control. The heating chamber, constructed from peek insulating polymer, has a diameter of 0.02 m and a total length of 1.5 m. Titanium oxide electrodes are used within the system. Voltage, current, power, and temperature data were simultaneously recorded in real time from the Programmable Logic Controller (PLC) using an Open Platform Communication (OPC) server (KepserverX) on a lab-based PC. The OPC communication facilitates read/write access to the PLC, the storage of real-time data trends, and the implementation of both classical and advanced controllers. The tomato basil sauce, initially prepared at room temperature, was heated to 90 °C at a constant flow rate of 1 L/min in the CFOH system. The heated sauce was then collected in the outfeed tank.

Although the ingredients of the tomato basil sauce contained a reasonable quantity of olive oil, the presence of salt and ionic spices was sufficient to significantly raise the electrical conductivity of the sauce. During the heating process, the temperature of the product was monitored using optic fiber temperature sensors positioned along the heating chamber. Additionally, a set of two thermocouples was used to measure the product infeed temperature and to validate the outfeed temperature. PID, MPC, and AMPC controllers were implemented in real time using the Open Platform Communication (OPC) server, interfaced with the Programmable Logic Controller (PLC) of the Continuous Flow Ohmic Heater (CFOH) system. The controllers were tasked with maintaining a target temperature of 90 °C. Energy efficiency was evaluated based on the time required to reach the set reference temperature, temperature precision, and system power consumption. Each controller was tested over a 6 min operation period to obtain the performance results.

2.3. Implementation of PID, MPC, and AMPC

Before implementing the controllers, it was necessary to calibrate both the power and the mass flow rate of the system. The calibration of the infeed pump was particularly important because the pump is regulated by a motor inverter housed within the CFOH control unit. The motor inverter adjusts the pump's flow rate by varying the frequency of the voltage applied to the pump. This calibration is ensures that, when a specific frequency is set, either manually or automatically by the controller, the corresponding flowrate is accurately achieved in L/min.

Secondly, the calibration of the HV (0–4.2 kV) thyristor was necessary to ensure the effective control of the RMS voltage (V_{rms}) delivered to the primary side of the transformer, which has a turns ratio of 1:10. A dimensionless input range from 1 to 100 was calibrated to correspond to a V_{rms} range from 0 to 415 V that exhibits a non-linear relation. The complete procedures for both calibrations are detailed in our previous publication [26].

These calibrations are then mapped and communicated with the PLC-based CFOH control unit using OPC technology. This approach allows seamless real-time data exchange and facilitates the direct deployment of controllers designed in the MATLAB/Simulink environment onto the PLC. Figure 3 shows the implemented plant controller architecture implemented to achieve and control the desired temperature for the processing of the tomato basil sauce sample.

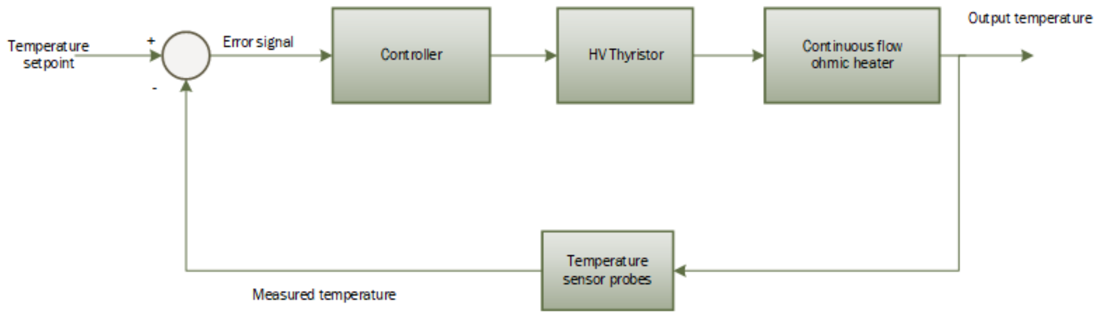

Figure 3. Controller and plant architecture.

2.3.1. Implementation of PID

PID controllers are commonly utilized for the control of closed-loop processes. In designing the PID controller, we considered a single input single output (SISO) system, where the primary regulated variable is the output temperature, while other process parameters, such as mass flow rate, are maintained at a constant level. The equation governing the PID controller is expressed as follows:

$$R(t) = K_p \cdot x(t) + K_i \int_0^t x(t)dt + K_d \frac{dx(t)}{dt} \tag{1}$$

The proportional term, K_p, is determined by the difference between the desired reference temperature and the actual measured value of temperature at each time step, effectively representing the temperature error. The integral term, K_i, $K_i \int_0^t x(t)dt$, accounts for the cumulative sum of past errors, while the derivative term, K_d, dx(t)/dt, evaluates the rate at which the error changes, helping to assess whether the error decreases. In this context, K_p helps to reduce the rise time, K_i addresses the steady-state error, and K_d improves the settling time and minimizes overshoot. The PID controller was configured using the Zeigler–Nicholas tuning method to obtain the proportional (P) gain of 2.5, an integral (I) gain of 0.2, and a derivative (D) gain of 0 [27]. To reduce the influence of noise, voltage limits were imposed on the controller, constraining its operational range. These voltage limits were determined based on real-time data, taking into account variations in electrical conductivity and the system's power requirements.

During the heating process, the product flow rate is maintained constant at 1 L/min. The PID controller is provided with a reference for the desired output temperature. The temperature at the outlet is monitored using two optical fiber temperature sensors positioned at the heater's outlet. Additionally, a thermocouple is placed outside the heating area to further validate the readings from the optical fiber sensors. The measured temperature is compared to the reference temperature, and the resulting error is fed into the PID controller. The PID controller then sends a dimensionless signal, ranging from 0 to 100, to the HV thyristor. This signal corresponds to a specific high voltage applied to the electrodes. The effective performance of the PID controller is achieved through careful tuning of the controller gains.

2.3.2. Implementation of MPC and AMPC

Model-based Predictive Control (MPC) is an advanced approach that employs the processing model to predict the future outputs of the model according to system behavior. At each time step, MPC determines the optimal control action by solving a constrained optimization problem, which takes into account predictions of future costs, disturbances, and constraints over a moving time horizon. This approach is often referred to as "receding horizon" control because the optimization process continually updates as new data becomes available. The fundamental concept is that short-term predictive optimization can lead to optimal long-term performance, as the prediction error remains smaller over short intervals compared to long-term predictions.

The key distinction between MPC and traditional control methods lies in its use of real-time prediction and optimization, rather than relying on precomputed control laws. However, a major challenge with MPC is the need to solve the optimization problem at every time step, which has historically limited its use to systems with slow sampling rates, typically below 1 Hz. Recent advancements, such as explicit MPC, address this limitation by solving the optimization problem analytically and storing the results in a lookup table, allowing for the rapid evaluation of the control policy. The MPC is mathematically represented by Equations (2) and (3).

$$x(k+1) = Ax(\mathrm{k}) + B_u u(\mathrm{k}) + B_v v(\mathrm{k}) + B_d d(\mathrm{k}) \tag{2}$$

$$y(k) = Cx(\mathrm{k}) + D_v v(\mathrm{k}) + D_d d(\mathrm{k}) \tag{3}$$

The matrices A, B_u, B_v, B_d, C, D_v, and D_d are parameters that can change over time. u is the control input or manipulated variable (MV), y is the plant output, x denotes the plant model states, v represents the measured disturbance, d is the unmeasured disturbance, and k represents the time index. A conventional MPC controller typically operates around a linearized and fixed nominal operating point (x), where the plant model determines the optimal control action (u). For the MPC applied in this study, the specific properties are outlined below:

$$A = \begin{bmatrix} 0.999 & 0.295 \\ -7.2 \times 10^{-4} & 0.970 \end{bmatrix},\ B_u = \begin{bmatrix} 8.27 \times 10^{-5} \\ 5.48 \times 10^{-4} \end{bmatrix},\ B_v = 0,\ B_d = 0, C = [1\ 0] \tag{4}$$

$$D_v = 0,\ D_d = 3.3 \times 10^{-4}.$$

Sample time ($\mathrm{t_s}$) = 0.3 s;
Rate of change of manipulated variable (Δu) = 2.78×10^{-4};
Output variable weight = 0.0011;
Prediction horizon = 30;
Control horizon = 3.

The control and prediction horizons were configured based on the residence time of the food product within the heating chamber. The prediction horizon was selected to account for the time required for the product to flow from the inlet to the outlet, as well as to accommodate the temperature build-up in the CFOH chamber. In contrast, the control horizon was defined to ensure that the controller could take corrective actions within the necessary time frame to maintain optimal heating conditions. Additionally, matrix coefficients and the weights for the manipulated and the output variables were selected based on the constraints and cost functions observed during real-time operation. These assessments build upon the controller design methodologies detailed in [26].

However, for an Adaptive Model Predictive Control (AMPC), the nominal operating point is continuously updated over time to align with the evolving plant model. This allows the operating point to vary as necessary to remain consistent with the updated system dynamics. The AMPC can be represented by the equations expressed in Equations (5) and (6).

$$x(k+1) = x_n + A(x(\mathrm{k}) - x_n) + B(u(\mathrm{k}) - u_n) + \Delta x_n \tag{5}$$

$$y(k) = y_n + C(x(\mathrm{k}) - x_n) + D(u(\mathrm{k}) - u_n) \tag{6}$$

For this AMPC, the parameter matrices represented by A, B, C, and D are updated over time; and x_n denotes the nominal operating point of the AMPC. Δx_n represents the nominal state increments, u_n is the nominal input, and y_n is the nominal output. For the AMPC implemented in this research, the same properties as those used in the MPC were applied, with the addition of nominal state increments Δx_n = 0.000278, y_n = 0.0010, and u_n = 20. The advanced process controls, including PID, MPC, and AMPC, were designed and developed prior to the experiment. The development of these controllers, along with the integration between MATLAB and the PLC-based CFOH unit, has been detailed in [7].

2.3.3. Energy Analysis

In the experiments, the tomato basil sauce was heated to 90 °C when PID, MPC, and AMPC controllers were independently deployed on the Continuous Flow Ohmic Heater. During the heating process, the flowrate of the tomato basil sauce was kept constant at 1 L/min. The measured infeed temperature of the sauce was 24 °C and the measured infeed electrical conductivity was 0.85 S/m. The energy analysis can be expressed as Equations (7)–(9).

$$\sum Energy_{in} = \sum Energy_{out} \tag{7}$$

$$\sum Energy_{in} = \dot{m}C_p(T_{in} - T_{room})_{\ in} + E_{electrical} \tag{8}$$

$$\sum Energy_{out} = \dot{m}C_p(T_{out} - T_{in})_{\ out} + E_{loss} \tag{9}$$

where $\sum Energy_{in}$ represents the total energy input to the CFOH, while $\sum Energy_{out}$ corresponds to the energy output due to the ohmic heating effect and the thermophysical properties of the food product. $E_{electrical}$ denotes the electrical energy supplied to the ohmic heater. The term $\dot{m}$ represents the mass flow rate, C_p is the heat capacity of the food product being heated, T_{in} is the inlet temperature of the food product entering from the infeed tank, T_{room} is the ambient room temperature, and T_{out} is the recorded outlet temperature. The energy losses, E_{loss}, considered in the system are due to thermal conduction to the applicators and heat dissipation at the titanium electrodes. These losses are quantified by Equation (10).

$$E_{loss} = \nabla\cdot(\mathrm{k(T)}\cdot\nabla\mathrm{T}) + \dot{m}C_{Ti}(T_{out} - T_{electrode})_{\ loss} \tag{10}$$

In Equation (10), C_{Ti} represents the heat capacity of titanium and $T_{electrode}$ denotes the initial temperature of the electrodes. The latent heat of vaporization is not taken into account since the only point of release is through the applicator outlet. The energy efficiency η is detailed in [13].

3. Results and Discussion

During the ohmic heating of the tomato basil sauce, the controller objectives are:

- Desired transient response to user temperature input: This ensures that the temperature rise within the heating chamber is not too fast or too slow. This goal also places emphases on eliminating temperature over-shoots in order to prevent boiling and pressure build up within the heating chamber.
- Desired steady-state response: This objective eliminates steady-state errors at the setpoint temperature.
- Robustness: This ensures that the CFOH has a stable and controllable response.

Figure 4 shows the temperature response of the CFOH when the tomato basil sauce was heated to a desired reference temperature of 90 °C using a PID controller. The electrical power supplied by the controller during heating is also shown as recorded by an onboard power meter in the control panel. The performance of the PID controller is shown by the deviation of the output temperature from the setpoint temperature. The trend of the energy efficiency was also shown. As seen in Figure 4, the rapid heating derived from OH was an advantage as the outfeed temperature is close to the setpoint of 90 °C in less than 2 min of run time.

Figure 5 shows the temperature response presented when the MPC controller is used for heating. The MPC controller has a shorter settling time of 90 s compared to that of the PID controller of 117 s, as shown in Table 1.

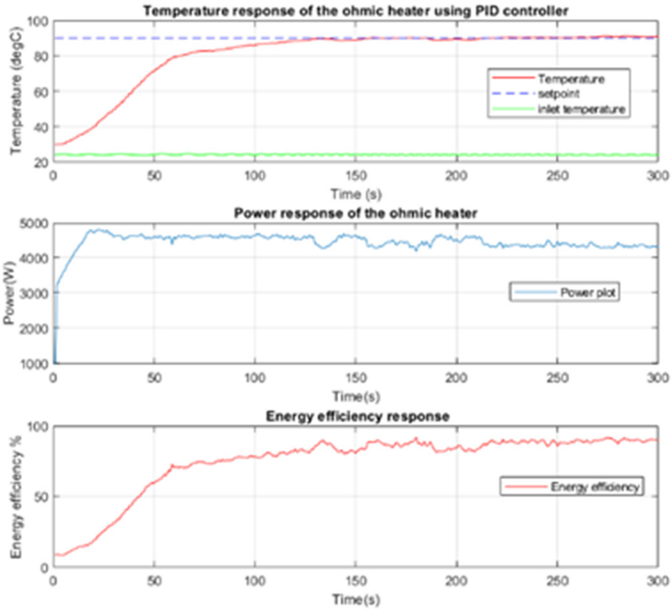

Figure 4. Temperature response of heating tomato basil sauce with the PID controller.

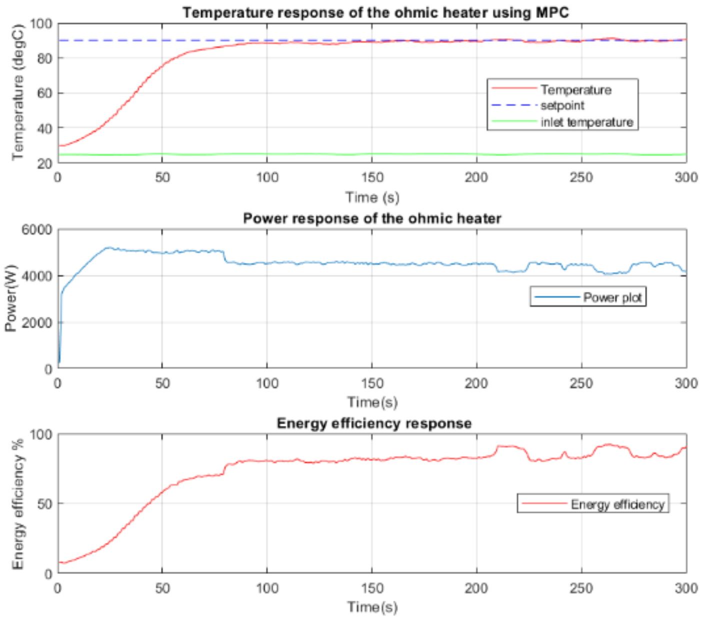

Figure 5. Temperature response of heating tomato basil sauce with the MPC controller.

Table 1. Performance comparison of the PID, MPC, and AMPC controllers.

Controller	Settling Time-2% Criteria (s)	Max. Overshoot (°C)	Max. Undershoots (°C)
PID	117	91.2	88.8
MPC	90	91.2	88.8
AMPC	76	91.6	89.7

The response from applying the AMPC controller is shown in Figure 6. The performance of the AMPC controller in terms of temperature transient time, steady-state error, temperature overshoots, temperature undershoots, and settling time exceed those of both the PID and MPC controllers. The settling time from the AMPC controller was observed to be 76 s—a much shorter time compared to the 117 s and 90 s of PID and MPC, respectively.

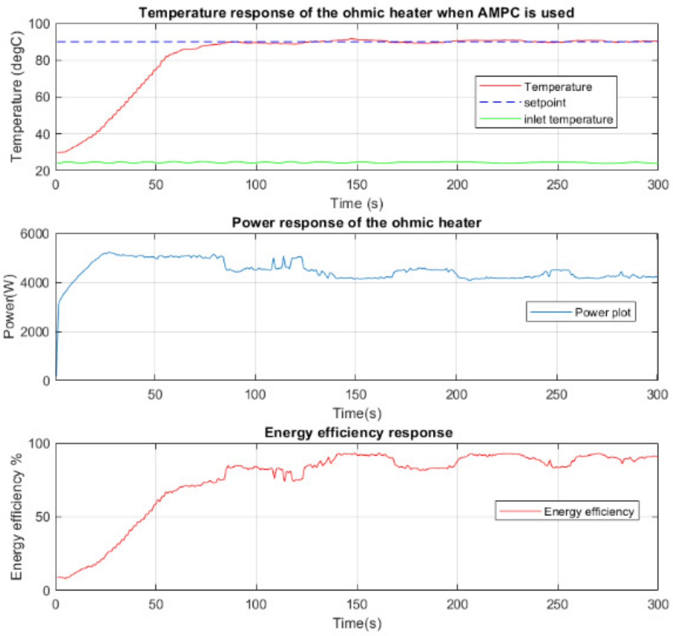

Figure 6. Temperature response of heating tomato basil sauce with the AMPC controller.

The performances of the PID, MPC, and AMPC controllers are further evaluated in Table 1 below based on the objectives of the controller. According to Table 1, the AMPC controller has the shortest settling time of 76 s, which indicates that the final and setpoint temperature of 90 °C is reached (with a 2% criterion) the quickest. The PID controller is the slowest to reach the setpoint, at 117 s. The performance of the PID and MPC controllers are similar in terms of the maximum overshoot and maximum undershoot temperature observed. With the AMPC, the maximum overshoot observed was 91.6 °C, which is higher than that of both MPC and PID. However, the AMPC has a higher maximum temperature undershoot of 89.7 °C, which indicates that the deviation from the setpoint temperature is the lowest compared to other two implemented controllers.

Table 2 shows the root-mean-square error (RMSE) of the temperature response of the PID, MPC, and AMPC controllers when compared to the temperature setpoint of 90 °C. The RMSE comparison is taken after the first 60 s of heating. From Table 2, the weighted average error between the setpoint temperature and actual temperature for the AMPC is 1.18, which is the lowest compared to the PID and MPC controllers. A low RMSE value of 1.18 indicates a good value when compared to 90 °C. This indicates less than 2% deviation from the setpoint temperature. In terms of performance comparison between the controllers, the AMPC has the lowest RMSE value.

Table 2. RMSE values of the PID, MPC, and AMPC controllers.

Controller	Setpoint Temperature (°C)	RMSE Value
PID	90	2.99
MPC	90	1.83
AMPC	90	1.18

Table 3 shows the mean energy comparison of the different controllers in Figures 4–6. The mean efficiency of the controller is recorded from 60 s to 300 s. The mean efficiency is taken after 60 s to ensure appropriate temperature build up within the heating chamber. Table 3 reveals that the conversion of electrical energy to heat with the CFOH is highest when the AMPC controller is adopted, compared to PID and MPC. This indicates that the rate of conversion of electrical energy to heat is the highest with AMPC. When heating up the tomato sauce (in the first 60 s), low energy efficiencies were observed for all three deployed controllers. This is due to the initial temperature building up within the heating chamber and the viscosity of the tomato sauce. The heating rate and energy efficiency conversion is generally low in the initial build up for product with a higher viscosity [1].

Table 3. Energy consumption and energy efficiency of the implemented controllers.

Time (s)	PID Power (KWh)	MPC Power (KWh)	AMPC Power (KWh)	PID EF (%)	MPC EF (%)	AMPC EF (%)
0–60	4.41	4.70	4.70	35.14	33.57	33.98
60–300	71.47	71.89	70.76	88.72	88.96	89.81

The faster heating rate of the CFOH comes with detrimental effects, such as temperature overshoots, uneven heating, boiling, and large steady-state errors. Hence, a steady rise in temperature is preferred. This steady rise in temperature is seen in Figures 4–6 and ensures the uniform heating of the tomato sauce and that the tomato sauce does not boil within the heating chamber. Therefore, the PID, MPC, and AMPC controllers were tuned to remove temperature overshoots for achieving the desired temperature profiles. The efficiency seen from the results does not take into consideration the energy loss in the positive displacement infeed pump. The energy dissipated in the pump is assumed to be isolated from the heating process.

The CFOH process demonstrated in this study shows a comparable results with the various heating technologies discussed in [28]. The study assessed several innovative and conventional food preservation methods, with the aim of evaluating and comparing the energy efficiency of high-pressure processing, microwave volumetric heating, ohmic heating, and conventional thermal treatments. Their findings indicated that energy efficiency for ohmic heating systems tends to improve as the scale of the equipment increases.

4. Conclusions

The results presented in this research suggest that the industrial application of Continuous Flow Ohmic Heating for tomato basil sauce can be a more sustainable and viable alternative to conventional heating methods. The heating experiments were conducted using tomato basil sauce prepared with pure tomato puree, basil, olive oil, and other spices proprietary to the recipe. A classical PID controller and advanced controllers (MPC and AMPC) were developed using a validated mathematical model, and were uniquely implemented using an OPC server via MATLAB/Simulink for effective control in real time. This study presents the first instance of obtaining and reporting such experimental results.

The experimental results established that the CFOH system has an energy conversion efficiency of at least 88.72%. Additionally, the analysis showed that this efficiency can be further increased by applying advanced controllers, such as MPC and AMPC. It was also observed that there were no significant differences in electrical power consumption when comparing PID, MPC, and AMPC controllers, indicating that the observed energy efficiency was largely a function of the controller performance.

Future work will focus on enhancing the CFOH system to include pasteurization and sterilization capabilities. Plans include adding holding tubes to assess the degree of lethality in comparison with conventional heating methods. Furthermore, the potential for heat recovery during the cooling phase of the food materials will also be explored.

Author Contributions: O.O.-o.: Methodology, Software, Validation, Formal analysis, Writing. T.J.: Writing—Review and Editing. M.H.: Supervision, Validation, Writing—Review and Editing. X.X.: Supervision, Validation, Writing—Review and Editing. M.R.: Writing—Review and Editing. H.Z.: Supervision, Conceptualization, Formal analysis, Resources, Writing—Review and Editing. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the EU Horizon 2020 SUSFOOD 2 MEFPROC project, under grant agreement No. 727473.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Acknowledgments: The authors would like to thank Ohm-E Technology (UK), Jonny Shepherd, and the NCEFE team at Sheffield Hallam University for the guidance received when performing the experiments.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Cappato, L.P.; Ferreira, M.V.; Guimaraes, J.T.; Portela, J.B.; Costa, A.L.; Freitas, M.Q.; Cunha, R.L.; Oliveira, C.A.; Mercali, G.D.; Marzack, L.D.F.; et al. Ohmic heating in dairy processing: Relevant aspects for safety and quality. *Trends Food Sci. Technol.* **2017**, *62*, 104–112. [CrossRef]
2. Silva, V.L.; Santos, L.M.; Silva, A.M. Ohmic heating: An emerging concept in organic synthesis. *Chem. Eur. J. Chem.* **2017**, *23*, 7853–7865. [CrossRef] [PubMed]
3. Joeres, E.; Ristic, D.; Tomasevic, I.; Smetana, S.; Heinz, V.; Terjung, N. Structure, Microbiology and Sensorial Evaluation of Bologna-Style Sausages in a Kilohertz Ohmic Heating Process. *Appl. Sci.* **2024**, *14*, 5460. [CrossRef]
4. Aydin, C.; Kurt, Ü.; Kaya, Y. Comparison of the effects of ohmic and conventional heating methods on some quality parameters of the hot-smoked fish pâté. *J. Aquat. Food Prod. Technol.* **2020**, *29*, 407–416. [CrossRef]
5. Sofi'i, I.; Arifin, Z.; Oktafrina. Energy consumption for patchouli oil extraction using ohmic heating. *IOP Conf. Ser. Earth Environ. Sci.* **2022**, *1012*, 12062. [CrossRef]
6. Alkanan, Z.T.; Altemimi, A.B.; Al-Hilphy, A.R.; Watson, D.G.; Pratap-Singh, A. Ohmic heating in the food industry: Developments in concepts and applications during 2013–2020. *Appl. Sci.* **2021**, *11*, 2507. [CrossRef]
7. Oluwole-ojo, O.; Zhang, H.; Howarth, M.; Xu, X. Energy consumption analysis of a continuous flow ohmic heater with advanced process controls. *Energies* **2023**, *16*, 868. [CrossRef]
8. Choi, W.; Kim, S.; Park, S.; Ahn, J.; Kang, D. Numerical analysis of rectangular type batch ohmic heater to identify the cold point. *Food Sci. Nutr.* **2020**, *8*, 648–658. [CrossRef]
9. Hassoun, A.; Siddiqui, S.A.; Smaoui, S.; Ucak, İ.; Arshad, R.N.; Garcia-Oliveira, P.; Prieto, M.A.; Aït-Kaddour, A.; Perestrelo, R.; Câmara, J.S.; et al. Seafood processing, preservation, and analytical techniques in the age of Industry 4.0. *Appl. Sci.* **2022**, *12*, 1703. [CrossRef]
10. Kim, S.S.; Park, S.H.; Kang, D.H. Application of continuous-type pulsed ohmic heating system for inactivation of foodborne pathogens in buffered peptone water and tomato juice. *LWT* **2018**, *93*, 316–322. [CrossRef]
11. Tumpanuvatr, T.; Jittanit, W. Quality improvement of refrigerated ready-to-eat cooked brown rice by adding gellan gum and trehalose with ohmic heating compared to conventional cooking method. *J. Food Process. Preserv.* **2022**, *46*, e16443. [CrossRef]
12. Cabas, B.M.; Icier, F. Ohmic heating–assisted extraction of natural color matters from red beetroot. *Food Bioprocess Technol.* **2021**, *14*, 2062–2077. [CrossRef]
13. Pelacci, M.; Malavasi, M.; Cattani, L.; Gozzi, M.; Tedeschi, F.; Vignali, G.; Rainieri, S.; George, S.; Zuber, F.; Mathiot, P.; et al. Impact of indirect and ohmic heating sterilization processes on quality parameters of apple puree: Application in a real industrial line. *J. Phys. Conf. Ser.* **2021**, *1868*, 012004. [CrossRef]
14. Hassoun, A.; Ojha, S.; Tiwari, B.; Rustad, T.; Nilsen, H.; Heia, K.; Cozzolino, D.; Bekhit, A.E.D.; Biancolillo, A.; Wold, J.P. Monitoring thermal and non-thermal treatments during processing of muscle foods: A comprehensive review of recent technological advances. *Appl. Sci.* **2020**, *10*, 6802. [CrossRef]
15. Hashemi, S.M.B.; Gholamhosseinpour, A.; Niakousari, M. Application of microwave and ohmic heating for pasteurization of cantaloupe juice: Microbial inactivation and chemical properties. *J. Sci. Food Agric.* **2019**, *99*, 4276–4286. [CrossRef] [PubMed]
16. Balthazar, C.F.; Cabral, L.; Guimarães, J.T.; Noronha, M.F.; Cappato, L.P.; Cruz, A.G.; Sant'Ana, A.S. Conventional and ohmic heating pasteurization of fresh and thawed sheep milk: Energy consumption and assessment of bacterial microbiota during refrigerated storage. *Innov. Food Sci. Emerg. Technol.* **2022**, *76*, 102947. [CrossRef]
17. Rebezov, M.; Farhan Jahangir Chughtai, M.; Mehmood, T.; Khaliq, A.; Tanweer, S.; Semenova, A.; Khayrullin, M.; Dydykin, A.; Burlankov, S.; Thiruvengadam, M.; et al. Novel techniques for microbiological safety in meat and fish industries. *Appl. Sci.* **2021**, *12*, 319. [CrossRef]
18. Ulpiani, G.; Borgognoni, M.; Romagnoli, A.; Di Perna, C. Comparing the performance of on/off, PID and fuzzy controllers applied to the heating system of an energy-efficient building. *Energy Build.* **2016**, *116*, 1–17. [CrossRef]
19. Shah, P.; Agashe, S. Review of fractional PID controller. *Mechatronics* **2016**, *38*, 29–41. [CrossRef]
20. Shamshirband, S.; Petković, D.; Enayatifar, R.; Abdullah, A.H.; Marković, D.; Lee, M.; Ahmad, R. Heat load prediction in district heating systems with adaptive neuro-fuzzy method. *Renew. Sustain. Energy Rev.* **2015**, *48*, 760–767. [CrossRef]
21. Yang, I.H.; Yeo, M.S.; Kim, K.W. Application of artificial neural network to predict the optimal start time for heating system in building. *Energy Convers. Manag.* **2003**, *44*, 2791–2809. [CrossRef]

22. Jun, Z.; Qiang, Z.; Yan-hong, C. August. Research on Energy-saving Regulation Model of Climate Compensation for Central Heating Station Based on Artificial Neural Network. In Proceedings of the 2020 Chinese Control And Decision Conference (CCDC), Hefei, China, 22–24 August 2020; pp. 2191–2197.
23. Drgoňa, J.; Arroyo, J.; Figueroa, I.C.; Blum, D.; Arendt, K.; Kim, D.; Ollé, E.P.; Oravec, J.; Wetter, M.; Vrabie, D.L.; et al. All you need to know about model predictive control for buildings. *Annu. Rev. Control* **2020**, *50*, 90–232. [CrossRef]
24. Ascione, F.; Bianco, N.; De Stasio, C.; Mauro, G.M.; Vanoli, G.P. Simulation-based model predictive control by the multi-objective optimization of building energy performance and thermal comfort. *Energy Build.* **2016**, *111*, 131–144. [CrossRef]
25. Sha, L.; Jiang, Z.; Sun, H. A control strategy of heating system based on adaptive model predictive control. *Energy* **2023**, *273*, 127192. [CrossRef]
26. Oluwole-ojo, O.; Javed, T.; Howarth, M.; Xu, X.; O'Brien, A.; Zhang, H. Model Validation and Real-Time Process Control of a Continuous Flow Ohmic Heater. *Modelling* **2024**, *5*, 752–775. [CrossRef]
27. Das, S.; Chakraborty, A.; Ray, J.K.; Bhattacharjee, S.; Neogi, B. Study on different tuning approach with incorporation of simulation aspect for ZN (Ziegler-Nichols) rules. *Int. J. Sci. Res. Publ.* **2012**, *2*, 1–5.
28. Atuonwu, J.C.; Leadley, C.; Bosman, A.; Tassou, S.A.; Lopez-Quiroga, E.; Fryer, P.J. Comparative assessment of innovative and conventional food preservation technologies: Process energy performance and greenhouse gas emissions. *Innov. Food Sci. Emerg. Technol.* **2018**, *50*, 174–187. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.