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A model-based control strategy for batch coffee roasting processes using a novel controlled variable

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ABSTRACT

It is desirable that batch coffee roasters be fully automated. This article offers an automation solution for industrial practitioners in the coffee industry, namely a control strategy for rotating-drum batch coffee roasters. The control strategy can be applied to standard PI-PID controller systems to automate artisan coffee roasters. It can consequently be implemented with minor adjustments to artisan batch coffee roasters that are currently in use. Controller parameters were experimentally determined using IMC, Cohen-Coon, and ITAE-based parameter techniques, and they were validated using Simulink®. Bode plots confirmed controller stability. The roasting process was classified as a lag-dominant, first-order plus time delay process and approximated; therefore, it was modeled as a pure integrating system. The batch roasting process was successfully controlled using a novel controlled variable, namely the roast profile derivative, and a final control strategy that switches between two loops is proposed for real-world application.

1. Introduction

1.1. Rationale

Controlling the coffee roasting process is non-trivial. An industry partner requested our research team to help automate semi-automated rotating-drum batch coffee roasting machines (hereafter referred to as “roasters”) that are operated manually by artisans. Automating these roasters would increase production rates, assist with artisanal training, make the process less labor-intensive, and replicate flavor profiles with greater ease. Thus, there is a need for a viable yet economical control strategy that fully automates these roasters. This paper addresses this need by proposing a novel control strategy that employs well-known and easily accessible controller systems.

Most studies aimed at finding solutions for controlling coffee roasting address the roasting process' modeling phase or sensory methods developed for real-time roast degree classification, with little emphasis on the actual development of the control strategy. Monitoring the degree of roast is essential for controlling batch roasters. Recent advances in monitoring include: real-time monitoring of the process with near-infrared spectroscopy using multivariate statistical analysis [1], laser mass spectrometry as an online sensor to determine the real-time degree of roast [2], and an increased interest in validating chemical indicators to monitor the degree of roast in real-time [3,4]. These sensors are, however, still in the developmental phase, expensive, and impractical to implement on currently employed roasters. In most real-world applications, thermocouples are used as temperature sensors to monitor the roast profile, which indicates the degree of roast to control the process manually; considering that most, if not all, artisan batch roasters employ this system, it is sensible to incorporate them into a control strategy [4]. Moreover, an artisan controls the temperature within the roaster to produce coffee with specific flavors. To facilitate manual control, step changes are induced in manipulated variables (such as heat flow, drum rotation speed, and air flow) during the coffee roasting process to apply manual control. The step changes' effect on the progression of the roasting process is ill-defined in the literature, creating the need for the development of a transfer function that enables control strategy development. This study developed such a transfer function and an affordable control strategy for batch roasters, which can be implemented at a low cost, as it enables readily available PI-PID units to be modified without manufacturing new process control equipment. The development of this strategy is underpinned by insights from recent studies on controller performance in thermal systems. Shuvo et al. [5] emphasizes the critical role of fine-tuning PI controller parameters to optimize performance,

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demonstrating that PID controllers, with properly adjusted gains, can achieve comparable results to PI controllers in terms of steady-state error and overshoot. This understanding underscores the importance of precise parameter adjustment in achieving effective process control.

In addition to the controller development this study investigated the controllability of the batch roasting process. The control objective was to reproduce a predefined roast profile according to the artisan's need. A valid mathematical model and transfer function of the coffee roasting process is required for developing a model-based strategy. The complexity of multiple, parallel chemical reactions that occur during the roasting process makes modeling the system non-trivial. However, a model for the heating of coffee beans during batch roasting was developed by Schwartzberg [6] and validated by Bopape et al. [7] and Uren et al. [8], which justified the model's ability to predict roast profiles accurately, making it applicable for this study. This model was constructed in Simulink® and used to analyze the performance of the experimentally developed control strategy. During experimentation, it was found that the roasting process may be approximated as a lag-dominant first-order process with a dead time of 20 s, yielding the process transfer function. Based on the definition of controllability proposed by Ziegler et al. [9] it was further found that the process is uncontrollable for the first 90 s of the roast. It is important to note that controllability is independent of the controller, and it is a characteristic of the process itself [9–12].

1.2. Background

The coffee roasting process is an irreversible heating process of green coffee beans that typically lasts for 10–20 min, depending on the desired degree of roast. It is a critical step in coffee production, considering that coffee beans are not consumed in their raw, green form. During roasting, the flavor, aroma, composition, and color of the beans are altered. These changes result from the Maillard and Strecker reactions, pyrolysis, and caramelization that occur during roasting. The process may be subdivided into the following main phases:

1) Drying: Moisture is lost (0–150 s)
2) Yellowing: The beans expand in volume and produce a bread-like aroma (150–350 s)
3) First crack: A popping sound is heard, and the beans reach the target temperature of 175–185 °C (at approximately 350 s)
4) Roast development: The degree of roast matures (350–530 s)
5) Second crack: A snapping sound is heard, and the beans reach the desired temperature of >200 °C (usually after 530 s)

1.3. In summary

This study classifies the batch coffee roasting process for control purposes and provides clarity regarding the effects of step changes induced on the roast profile during roasting. It also employs readily available sensor equipment (thermocouples) used by artisans within roasters in combination with PID controllers, which are often installed but underutilized and ill-adapted, to develop an implementable control strategy for batch rotating-drum roasters. Manufacturing companies can follow this strategy for the development of a controller that can be seamlessly integrated with the roasters that are currently in use. This paper first details the experimental methodology, followed by the controller design and performance. Limitations and future perspectives are then discussed before the final control strategy is offered, ending with the conclusions and recommendations.

2. Materials and methods

The controller parameters for the proposed control strategy were determined experimentally and the final control strategy was validated using simulation results. The following section explains the materials and equipment that were used during the experimentation to produce data for the controller design phase, followed by a discussion of the relative gain array (RGA) development. The RGA was set up to determine the optimal variable pairing, which saved time spent on physical experimentation. Lastly, the procedure followed during experimental runs is detailed. A process model is required to develop a model-based control strategy. In order to design and validate the designed controller a semi-physical model, developed by Schwartzberg [6] was reconstructed in Simulink® in this study, the model and its implementation within the Simulink® platform is detailed in Appendix A.

2.1. Experimental set-up

The Brazil-cultivated green beans roasted during the experimentation were Brazil Santos unwashed Arabica beans. The beans grew at altitudes of 600–1000 m in a tropical climate and had an average overall moisture content of 9.09 wt% prior to roasting.

Experiments were conducted on a Genio 6® Artisan coffee roaster (depicted in Fig. 1) comprising a perforated rotating drum with a 6 kg green bean capacity, which is rotated over a 25 kW open-flame liquid petroleum gas (LPG) burner. The LPG burner functions as the only heat source in the system; it heats air over a flame which then enters the drum to provide convection heating for the roasting process. The various components of the roaster (indicated with numeric values in Fig. 1), are listed in Table 1. The roasting and cooling fans have a specification of 660 m^3/h at 1100 Pa and 1000 m^3/h at 1600 Pa, respectively. Table 2 lists the measurement instrumentation that was used during the experimentation.

2.2. Variable pairing for control: The bristol RGA

Once control objectives are set and a model is acquired, identifying the best pairing of input and output variables for decentralized control follows. For a system with an $n \times n$ input-output model, $n!$ potential pairings exist [13]. To validate the experimental approach, this study employs RGA analysis. RGA reveals the pre-experiment pairing and selection of controlled variables. To control the process effectively, this optimization aims to reduce the number of experiments while

Fig. 1. Rotating drum batch artisan coffee roaster used during the experimentation.

Table 1
Artisan roaster components.

Component number	Component name	Description
1	Control panel	Siemens S7-1200 PLC controller
2	Gas burner	Fed with LPG gas to heat the system
3	Roasting drum	Roasting chamber, houses the bean batch
4	Roasting fan	Draws air through the system
5	Exhaust duct	Duct connecting the drum to the roasting fan
6	Cyclone	Removes particulate matter from the exhaust air stream
7	Chaff bin	Captures the solid particles from the cyclone
8	Bean hopper	Entrance point of the beans into the roasting drum
9	Sampling port & cup	Hand-held, extractable bean sampling cup
10	Cooling bin	Rotating container to cool beans rapidly after roast
11	Cooling fan	Draws air past the cooling bin to accelerate the final cooling step

Table 2
Measurement instrumentation used during experimentation.

Instrument	Application	Resolution (Maximum)
Type K thermocouples	Temperature measurements of environmental air and the bean batch.	0.025 °C (1370 °C)
Data logger: Pico technologyUSB TC-08	Logs online temperature profiles and stores data in a compatible computer file.	0.025 °C (1370 °C)
Kern laboratory balances	Weigh the bean batch for roasting purposes.	1 g (6000 g)
Fluke 922 Airflow meter	Measure the gas flow through the system.	1 m^3/h (99 999 m^3/h)

maximizing the variable pairing quality.

Initially, four process parameters were identified from the literature as the grouping of parameters to be included in the RGA analysis. These are:

1) The rate of temperature change of the bean batch ($\dot{T}_{roast}$)
2) The roast profile, or temperature versus time curve during the roast (T_{roast})
3) The flow rate of LPG to the burner (F_{gas})
4) Air flow rate through the system (F_{air})

$\dot{T}_{roast}$ and T_{roast} were identified as the controlled variables; whereas F_{gas} and F_{air} were to be manipulated to reach the control objective, which is the replication of roast profiles. The data required for the RGA were produced by the Simulink® process model (detailed in Appendix A).

For the current 2×2 process system, Seborg et al. [13] notes that the RGA is provided in matrix form by:

$$\Lambda = \begin{bmatrix} \lambda_{11} & \lambda_{12} \\ \lambda_{21} & \lambda_{22} \end{bmatrix} \tag{1}$$

Each λ value is defined as the open-loop gain in relation to the closed-loop gain for a particular pairing of variables and denoted by Eq. (2), C values denote controlled variables; whereas, M values denote manipulated variables within the process.

$$\lambda_{ij} = \frac{(\partial C_i / \partial M_j)_M}{(\partial C_i / \partial M_j)_C} = \frac{open\ loop\ gain}{closed\ loop\ gain} \tag{2}$$

The average gradients of the environmental air temperature that resulted from a 50 % step change increase in the LGP flow rate were determined experimentally for five priming temperatures (170, 180, 200, 210, and 230 °C). These experimentally determined gradients were then used in the Simulink® model in order to simulate a step change in the LPG flow to the burner, and the effect on the controlled variables ($\dot{T}_{roast}$ and T_{roast}) could be obtained as direct simulation output values. In turn, the effect of a step change from 43 to 50 kg s^{-1} in the second manipulated variable, namely air flow rate (F_{air}), could be simulated directly in the Simulink® model in order to determine the effect on the two main controlled variables. These simulation outputs were used to calculate the RGA matrix, as noted by Eq. (1). The final RGA was determined as:

$$\Lambda_{roast} = \begin{bmatrix} 0.74 & 0.26 \\ 0.26 & 0.74 \end{bmatrix} \tag{3}$$

These results were interpreted using the five cases regarding the interpretation of an RGA analysis and the four strategies mitigating loop interaction, provided by Seborg et al. [13]. The final suggested pairing is to control $\dot{T}_{roast}$ with F_{gas} and T_{roast} with F_{air}. Large control loop interaction results from one controlled variable being a direct function of the other; therefore, a switch-over control strategy is recommended instead of two independent control loops.

2.3. Experimental procedure

The RGA results were used to design the experimental plan. The experiments were focused on investigating how heat flow manipulation influences the roast profile. The derivative of the roast profile was calculated from the recorded experimental roast profile data to analyze the effect of the induced step changes on the rate of change of bean temperature.

The roaster is prepared for experiments by heating the empty drum's interior to the initial roasting temperature. The spinning drum is pre-heated, and once this prime temperature is reached, a single 6 kg batch of green beans is introduced into it through the bean hopper. At which point, the roasting process begins. After the process has started step changes in LPG flow are induced at selected time instances. Once the roasting process is complete, the beans are extracted from the rotating drum by allowing them to fall into the cooling tray. The cooling tray's raking arms begin to rotate; at the same instance, a continuous flow of air is drawn through the cooling tray. Note that the Siemens S7-1200 programmable logic controller (PLC) is inactive during the roasting process and its operation is limited to the priming phase. During the priming phase (that merely preheats the roaster) the PLC maintains a consistent air temperature within the empty rotating drum before the beans are introduced. The position of the LPG burner relative to the drum, roasting fan speed, drum rotation speed, the final roast temperature, and the magnitude of the step change were all kept constant and at a maximum throughout the experimentation. Table 3 summarizes the executed experimental plan.

Table 3
Executed experimental plan based on the RGA results.

Initial roast (prime) temperature	Step change	Time of step change	Number of roasts
170, 180, 200, 210, 230 °C	Step LPG 50–100 %	30 s	5
170, 180, 200, 210, 230 °C	Step LPG 50–100 %	50 s	5
170, 180, 200, 210, 230 °C	Step LPG 50–100 %	90 s	5
170 °C	Step LPG 100-50 %	240 s	1
170, 180, 200, 210, 230 °C	Step LPG 50–100 %	240 s	5
170, 180, 200, 210, 230 °C	Step LPG 50–100 %	300 s	5
170 °C	None (Control experiment)	–	3

2.4. Data analysis

To effectively compare the findings, baseline roast profiles were established as benchmarks. For each prime temperature, an average baseline roast profile was constructed from three individual roasting runs with no induced step changes. These baseline roasts represent the unregulated behavior of the controlled variable. The derivative of the baseline roast profile served as the reference for assessing how $\dot{T}_{roast}$ deviates from the general, unregulated behavior when a heat flow step change is introduced. Fig. 2 displays the baseline roast profiles and $\dot{T}_{roast}$ curves for prime temperatures of 170, 180, and 200 °C, respectively.

3. Controller design and performance

3.1. Controller design

It was found experimentally that $\dot{T}_{roast}$'s response to an induced heat flow change follows a first-order pure integrator behavior at specific time intervals during roasting. This behavior emerges only after the initial 90 s of the roasting process. Prior to this time frame, the process displays a clear first-order pattern with a time delay, indicating lag-dominant characteristics. According to Ruscio [10], first-order plus time delay processes with lag-dominance can be approximated using a first-order pure integrator transfer function. Fig. 3 depicts the pure integrator response of $\dot{T}_{roast}$. The results indicate that a step change in the LPG flow resulted in pure integrator behavior by the controlled variable ($\dot{T}_{roast}$) for step changes induced after 90 s.

A combination of the roasting process model and empirical data was used to determine the process transfer function. The transfer function was derived from the behavior of the selected controlled parameter and the rate of change of roast temperature ($\dot{T}_{roast}$), and it is provided by Eq. (4). The RGA results affirmed the suitability of integrating a switch-over control strategy when using $\dot{T}_{roast}$ as the primary controlled parameter. This section expounds the formulation of the primary control loop, which was designed to replicate predefined roast profiles. The average dead time (θ) was determined experimentally for each prime temperature, and an overall average value was used as the final θ value.

$$G_{p(roast)} = \frac{Ke^{-\theta s}}{s} \tag{4a}$$

$$G_{p(roast)} = \frac{(3.29 \times 10^{-4})e^{-20s}}{s} \tag{4b}$$

Based on the process transfer function, it was decided to investigate the suitability of a PI-PID controller for the current control objective. Three controller design methods, namely IMC, Cohen-Coon, and ITAE, were used, and their respective performances were compared to evaluate which approach would suit the controller best.

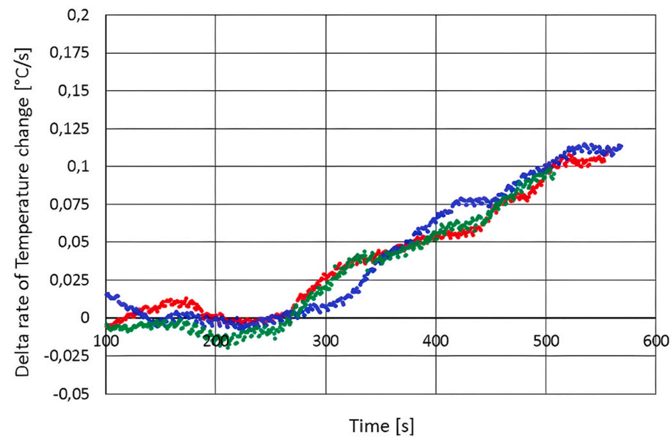

Fig. 3. Pure integrator response of $\dot{T}_{roast}$ to step change at 240 s; 170 °C (●), 180 °C (●), 200 °C (●).

The K value used in the IMC-based method was determined by calculating the overall average gradient of the process gains. This averaged value was determined by graphically calculating the average gradient of both the experimental and simulated data for each experiment conducted. The first-order with time delay behavior of the process allowed the average process gain value (K_p) to be determined, which is used in the Cohen-Coon and ITAE design methods. Table B.1 summarizes the average dead times and gradient values that were obtained and consequently used to determine the IMC-based parameters. Table B.2 summarizes the required process gains and process responses that are required to determine the Cohen-Coon and ITAE-based parameters. The final calculated controller parameters are provided in Table 4.

Table 4
Final controller parameters.

PI controller parameters						
—	IMC		Cohen-Coon		ITAE	
	Average	Maximum	Average	Maximum	Average	Maximum
K_c	112.53	221.90	685.58	685.58	408.56	408.56
τ_I	60.80 s	69.60 s	23.06 s	26.40 s	23.43 s	26.82 s
PID controller parameters						
—	IMC Average	Maximum	Cohen-Coon Average	Maximum	ITAE Average	Maximum
K_c	200.05	394.48	1103.90	1103.90	672.80	672.80
τ_I	60.80 s	69.60 s	36.67 s	41.98 s	31.20 s	35.72 s
τ_D	8.44 s	9.67 s	6.24 s	7.14 s	6.24 s	7.15 s

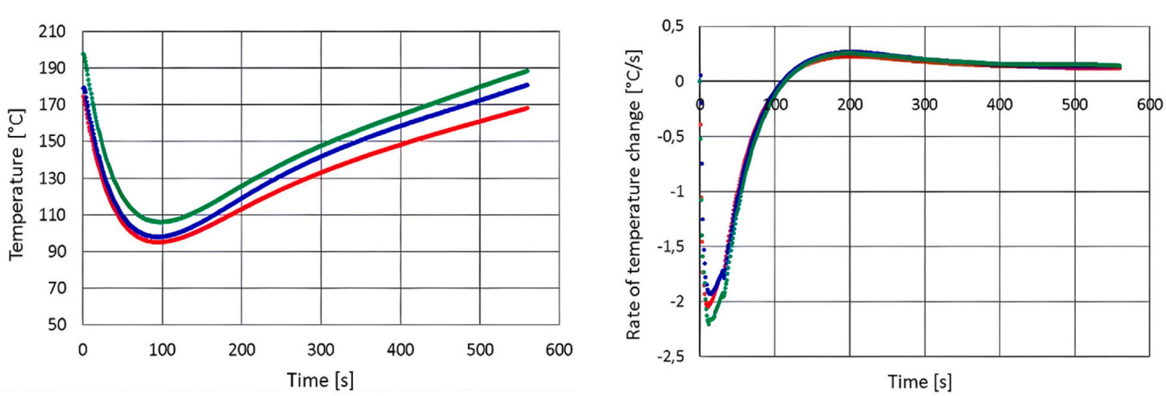

Fig. 2. Average benchmark curves for roast profiles and $\dot{T}_{roast}$; 170 °C (●), 180 °C (●), 200 °C (●).

3.2. Controller performance

Incorporating these controller parameters, the controller's performance was assessed within the Simulink® platform and the simulation results were compared to determine the best performing controller parameters. The controllers showed varying degrees of performance. The PI controllers outperformed the PID controllers, which exhibited instability in the presence of system dead time. Specifically, the IMC-based PI controller demonstrated superior performance, handling the dead time effectively and stabilizing the process within 20 s.

The controller was unable to handle any dead time within the system and showed instability when using the maximum parameter values obtained from the IMC, Cohen-Coon, and the ITAE methods. In contrast to this observation Figs. 4–7 illustrate the controller performance when the averages of the parameter values were used rather than the maximum values. The PI controllers outperformed the PID controllers in this application even though Shuvo et al. [5] has reported that PID controllers exhibit similar performance to PI controllers under various conditions. It is however evident that PID controllers were unable to stabilize the batch roasting process in the presence of dead time, deeming it unsuitable for batch roasting applications. All the PID controllers showed similar behavior to that seen in Fig. 5.

The IMC-based PI controller demonstrated superior performance. Its average parameter values were fine-tuned to evaluate the controller's ability to reach the set point value within 20 s, validating the controller's ability to handle the amount of dead time present in the system. The controller parameters were fine-tuned by analyzing the Bode plots (provided in Fig. 8) and by adjusting the parameters accordingly. Larger τ_I resulted in greater controller stability at higher frequency values. The final, fine-tuned controller used a K_c parameter value of 112.53, and the τ_I was adjusted to 6841.58 s. Fig. 9 illustrates its superior performance and ability to stabilize the process within a time frame smaller than the dead time when multiple step changes are induced.

3.3. Comparative controller analysis

This study investigated three controller design methods: IMC-based, Cohen-Coon, and ITAE for their applicability in controlling the coffee roasting process. Each method presents unique advantages and disadvantages, impacting their performance in real-world applications.

The IMC-based PI controller demonstrated superior performance, particularly in handling the inherent dead time present in the coffee roasting process. Its robustness to process variations and disturbances makes it a strong candidate for industrial implementation. The key advantage of the IMC-based PI controller is its ability to stabilize the process within 20 s, which is critical for maintaining consistent roast quality. However, the complexity of tuning the IMC parameters can be a disadvantage, requiring a thorough understanding of the process dynamics.

On the other hand, the Cohen-Coon method offers a simpler approach to controller design, which can be advantageous in terms of ease of implementation. This method provides a good initial parameter setting that can be further fine-tuned based on empirical data. However, its performance is less robust compared to the IMC-based PI controller, particularly in the presence of significant process delays and disturbances. The Cohen-Coon method tends to result in a more aggressive controller, which can lead to overshooting and oscillations in the controlled variable.

The ITAE method aims to minimize the integral of the time-weighted absolute error, focusing on reducing long-term deviations from the setpoint. While this approach is effective in achieving smooth and stable control with minimal steady-state error, it can result in slower response times. The ITAE-based PI controller exhibited a slower stabilization compared to the IMC-based PI controller, which may not be ideal for processes requiring rapid adjustments. Additionally, the ITAE method's performance can be highly sensitive to accurate process modeling, which can be a limitation if the process dynamics are not well understood or are subject to significant variability, as is the case with the batch roasting process.

In summary, the IMC-based PI controller stands out for its robustness and quick stabilization, making it suitable for the dynamic nature of coffee roasting. The Cohen-Coon method, while easier to implement, may require further fine-tuning to avoid aggressive control actions. The ITAE method offers stability and minimal steady-state error but at the cost of slower response times.

4. Limitations and future perspectives

4.1. Uncontrollable time frame of the coffee roasting process

During the initial experimental runs, it was noted that the controlled variable reacts in one way when step changes are induced within the first minute of operation, and another way when step changes are induced closer to the middle and end of a roast. This observation led to an additional analysis that could establish the time frame at which the process is controllable when the derivative of the roast profile is used as the controlled variable, rather than the traditional roast profile. The findings indicated a distinct time frame within the coffee roasting process that aligns with the criteria of uncontrollability outlined by Ziegler et al. [9], Skogestad et al. [11] and Faanes [12]; the controllability of a process is defined as the ability of the process to achieve and maintain the desired equilibrium value. It is important to note that controllability is independent of the controller, and is a characteristic of the process itself.

Within the first 90 s of the roasting process, $\dot{T}_{roast}$ exhibits multiple oscillations within 20-s intervals, as illustrated in Fig. 10. This figure

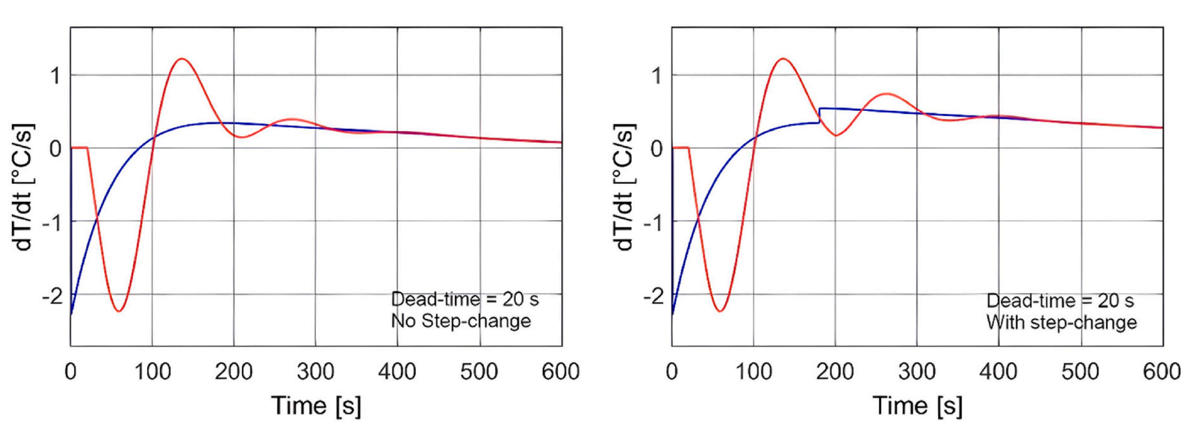

Fig. 4. Controller performance of IMC-based PI controller using averaged parameter values; Set point (—), Process output (—).

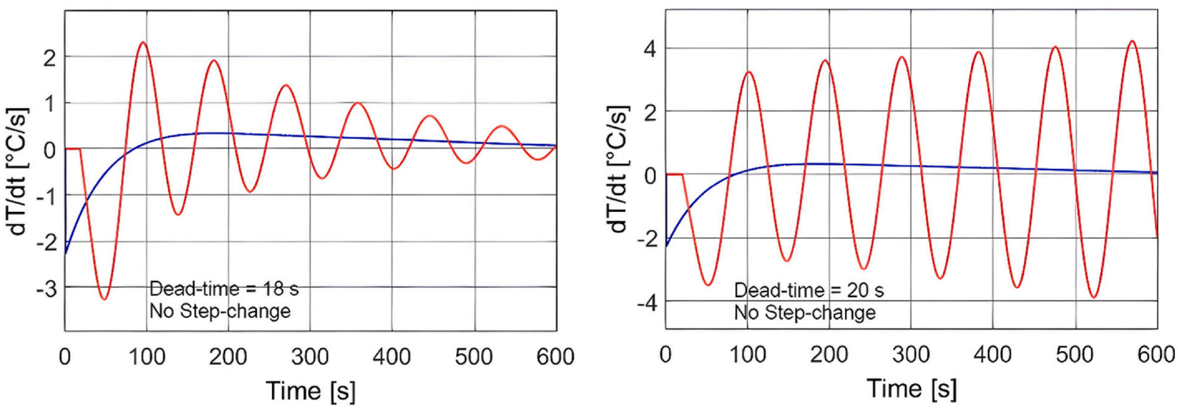

Fig. 5. Controller performance of IMC-based PID controller using averaged parameter values; Set point (—), Process output (—).

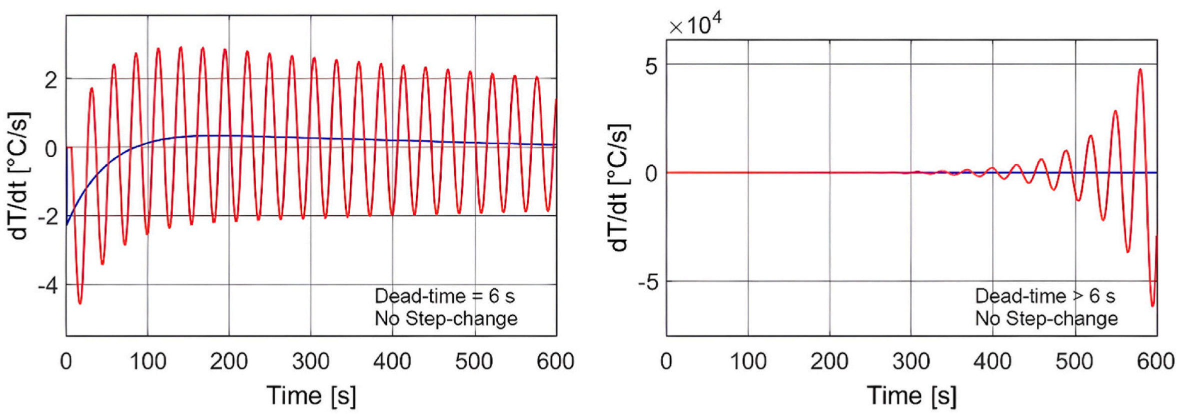

Fig. 6. Controller performance of Cohen & Coon based PI controller using averaged parameter values; Set point (—), Process output (—).

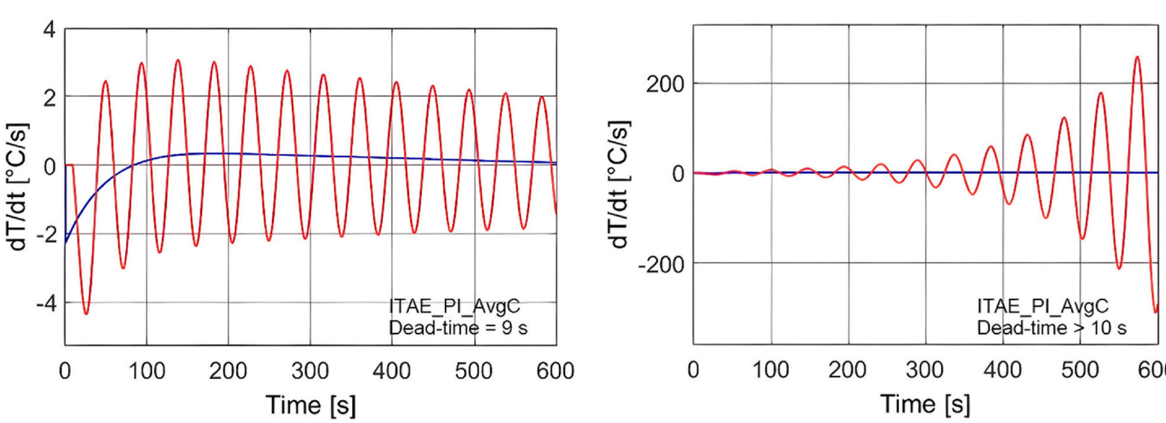

Fig. 7. Controller performance of ITAE-based PI controller using averaged parameter values; Set point (—), Process output (—).

captures the unregulated response of the controlled variable, showcasing its rapid variability. The average dead time for the roasting process to respond to step changes was determined as 20 s. This substantial input time delay coupled with rapid fluctuations in the roast profile gradient ($\dot{T}_{roast}$), which are caused by evaporative cooling occurring during the first 150 s of coffee roasting, results in limited controllability during the initial 90 s of the process. This hampers the controller to effectively stabilize the process. The process responds to the controller's action from the preceding 20 s, during which time frame multiple variations in the process variable have occurred, decreasing controller efficacy. The uncontrollable period aligns with the time frame preceding the roast profile's inflection point. This phase is indicated by the point of intercept on the roast profile derivative ($\dot{T}_{roast}$) graphs.

Roasting experiments were conducted to validate the identified uncontrollable process time frame. These experiments were conducted at prime temperatures of 170, 180, 200, 210, and 230 °C, introducing step changes at 30, 50, and 90 s after process initiation. A single step change involved a change in LPG flow capacity of 50 %–100 %. Fig. 11 illustrates the response of $\dot{T}_{roast}$ to these step changes (deviation from unregulated behavior) at a 170 °C prime temperature. These three response curves follow the same trend, despite each response representing an experimental run with distinct step change times. All step changes were

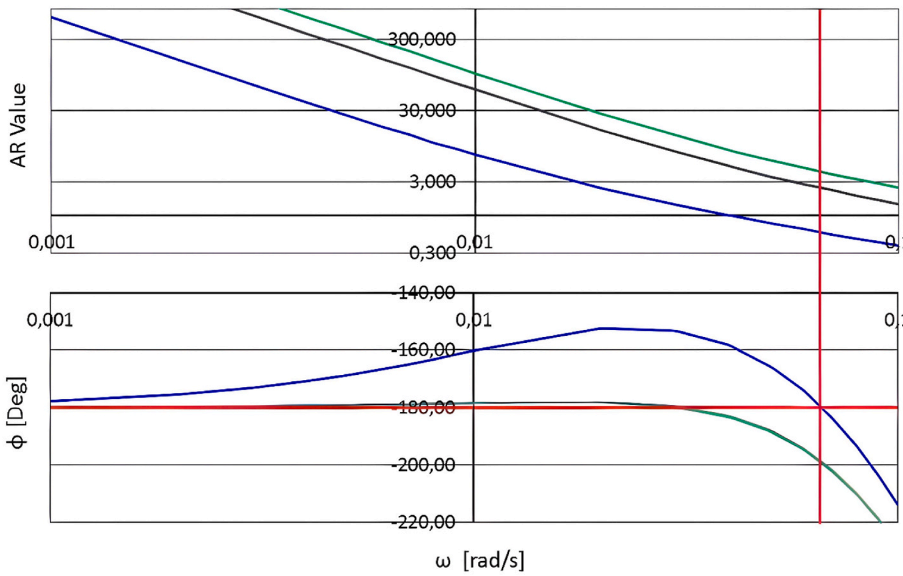

Fig. 8. Bode plots for average parameter PI controllers; IMC-PI (—), Cohen & Coon-PI (—), ITAE-PI (—).

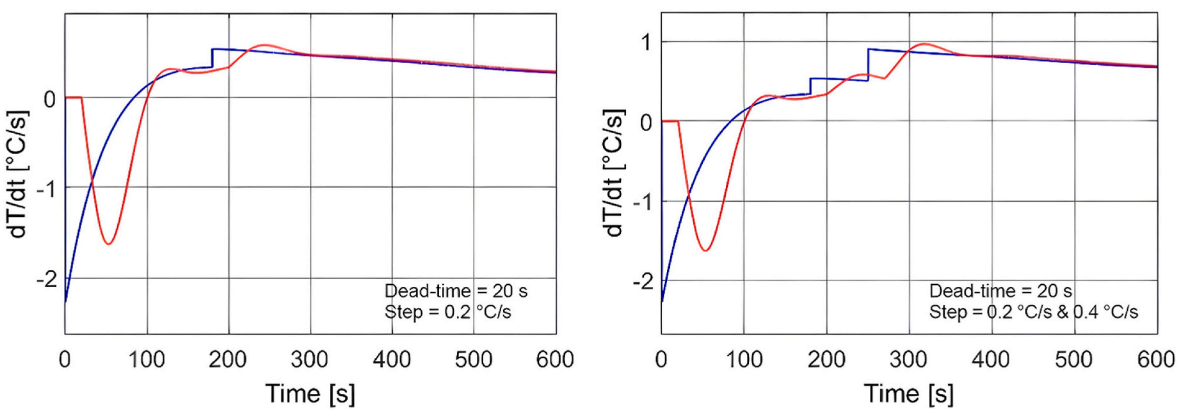

Fig. 9. Final controller's performance: 20 s dead time with step changes; Set point (—), Process output (—).

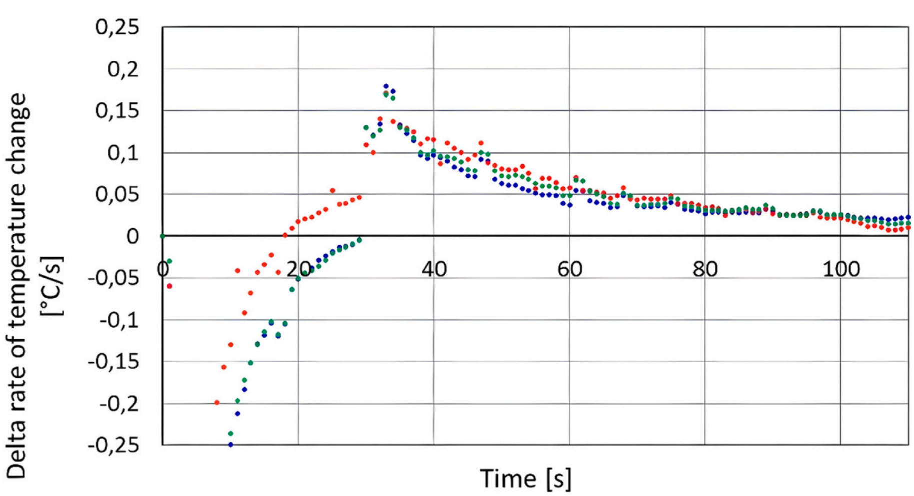

Fig. 10. Initial unregulated behavior of $\dot{T}_{roast}$ at 170 °C prime temperature; Run 1 (●), Run 2 (●), Run 3 (●).

induced within the uncontrollable process time frame, being the initial 90 s of the roast. This implies that controller action that occurs prior to the 90 s mark during roasting will not influence the roast profile or its derivative, which shows that manipulating the driving force behind the coffee roasting reaction (i.e. the heat addition) does not affect the progression of the roast during this time frame.

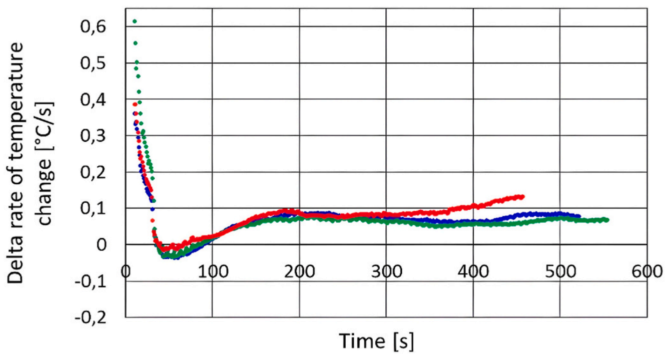

Fig. 11. Response of controlled variable on induced step change for roasts conducted at 170 °C prime temperature; 30 s Step (●), 50 s Step (●), 90 s Step (●).

This uncontrollable time frame is a limitation of the proposed control strategy. This phase is characterized by rapid and substantial oscillations in the controlled variable, $\dot{T}_{roast}$, due to the evaporative cooling effects occurring during the early stages of roasting. As a result, any controller action taken within this time frame is ineffective, as the process does not respond predictably to changes in the manipulated variable. This uncontrollability is inherent to the roasting process and is not dependent on the type of controller used.

The impact of this limitation is that the control strategy must remain passive for the first 90 s, only becoming active once the process enters a more stable and predictable phase. This uncontrollable period poses a challenge for achieving consistent roast profiles, as any variability during this phase can affect the final product quality. Furthermore, the initial 90 s lag also limits the ability to make real-time adjustments based on early-stage observations, necessitating a more reactive rather than proactive control approach during the initial roasting stages.

4.2. Future perspectives

The promising results of our control strategy for batch coffee roasting processes pave the way for several avenues of future research. One of the next steps is to explore and develop new control techniques that can further enhance the precision and efficiency of the roasting process. Advanced control algorithms such as model predictive control (MPC), adaptive control, and fuzzy logic control could be investigated to address the limitations identified in the current strategy, particularly the uncontrollable initial 90 s of the roasting process.

Another significant direction for future research is adapting the proposed control strategy to other types of coffee roasters, such as fluidized bed roasters and continuous roasting systems. Each type of roaster presents unique challenges and opportunities, and developing tailored control strategies for these systems could greatly enhance their automation and efficiency.

Research into integrating advanced sensors and real-time monitoring tools with the control strategy can also yield significant benefits. Innovations in sensor technology, such as near-infrared spectroscopy and laser mass spectrometry, could provide more accurate and immediate feedback on the roasting process, allowing for finer control adjustments and better end-product quality. Furthermore, the impact of different environmental conditions, such as humidity and ambient temperature, on the roasting process and control strategy effectiveness should be studied. Understanding these factors can help in developing adaptive control systems that maintain optimal performance under varying conditions.

In summary, the future perspectives for this research include exploring advanced control techniques, adapting the strategy to various types of coffee roasters and manufacturing processes, integrating cutting-edge sensor technologies, and investigating environmental influences. These efforts will contribute to the continuous improvement of coffee production, ensuring high-quality, consistent, and efficient coffee manufacturing practices.

5. Final control strategy

In order to define the final control strategy that will be implemented by using the developed controller parameters, it is important to realize that different roast profiles can have the same gradient during the roasting process. Unfortunately, this means that even if the controller controls the derivative (i.e. the gradient) of the roast profile perfectly, the controller will not necessarily replicate the desired roast profile and meet the controller objective. Therefore, in accordance with the RGA recommendations in Section 2.2, and considering the uncontrollable time frame of the process, the following switch-over strategy is proposed for real-world controller application: Take no controller action for the initial 90 s of the roast and employ a secondary loop (which uses the desired roasting profile as the set point and the heat flow into the system as the manipulated variable) to control the system from 90 to 140 s during roasting. This is done to ensure that the correct roast profile is replicated, and to warrant that controller action has indeed affected the controlled variable. After this time frame, control is governed by the primary loop, which employs the derivative of the roast profile as the controlled variable and the heat flow as the manipulated variable.

6. Conclusions

In this study, we developed an economical and viable control strategy that holds significant value for industrial practitioners in the coffee roasting industry, particularly in the automation of roaster operations. The key elements of our strategy include the use of a novel controlled variable, a pre-defined roast profile derivative, and an IMC-based PI controller with a K_c value of 112.53, and τ_I value of 6841.58 s. These elements have proven effective in applying process control, and the fine-tuned parameter values can be readily used to tune PI controllers for real-world applications. The coffee roasting process was classified as a lag-dominant first-order plus time delay system, which can be approximated and modeled as a pure integrating system. This modeling approach provides a validated transfer function for the batch roasting process, paving the way for future controller development. A significant finding of our study is the identification that the first 90 s of the batch roasting process are uncontrollable. Despite this limitation, our final control strategy presents a viable solution by implementing a switch-over strategy. This involves taking no controller action for the initial 90 s and then employing a secondary loop to control the system from 90 to 140 s to ensure that the correct set point is selected by the controller. The governing control loop then switches to the primary control loop that uses the novel controlled variable, the roast profile derivative, for the duration of the process.

The implications of this study are substantial for the coffee roasting industry. The control strategy can be applied to batch roasters currently in use, facilitating increased production rates, improved flavor profile replication, and reduced labor intensity. This makes the process more efficient and accessible for artisanal training and operations. However, there are limitations to our research. The uncontrollability of the initial 90 s of the roasting process raises questions about its impact on overall controller efficacy. Further research is needed to fully understand the effects of this uncontrollable period on various control strategies. Additionally, while our proposed strategy has shown promising results, real-world application may present unforeseen challenges that require further refinement and adaptation of the control parameters. Future research should focus on exploring the impact of the uncontrollable initial period in more detail, possibly investigating alternative control strategies that can mitigate its effects. Additionally, expanding the applicability of the control strategy to different types of coffee roasters and varying roasting conditions would provide broader validation of our findings. Further development of advanced sensors and real-time monitoring tools could also enhance the precision and effectiveness of the control strategy, making it even more robust for industrial applications.

In conclusion, our study provides a foundation for the automation of batch coffee roasting processes, offering a practical and cost-effective control strategy. Continued research and development in this area will further enhance the capabilities and efficiency of coffee roasting operations, benefiting both industrial practitioners and consumers.

CRediT authorship contribution statement

Cecilia M. Botha: Writing – original draft, Validation, Software, Methodology, Formal analysis, Conceptualization. **Abraham F. van der Merwe:** Writing – review & editing, Resources, Project administration, Funding acquisition, Data curation, Conceptualization. **Kenneth R. Uren:** Writing – review & editing, Supervision.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to reorder text, combine sections and clarify self-produced text. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Coffee roasting process model

As stated in the introduction, developing a model-based control strategy requires a process model of the process to be controlled. Schwartzberg's [6] semi-physical model, constructed in Simulink®, is used in this study; it has the ability to predict a coffee bean batch's temperature and moisture content. This model correlated extremely well with the roast profile obtained from experimental results in a different study [8]. The largest difference between the modeled and actual temperatures was a mere 2 °C [6,8]. Therefore, despite the model's less accurate moisture content prediction, it accurately predicts the bean batch's temperature throughout the roast. To clearly detail the equations used, each subsystem within the Simulink® model illustrated in Fig. A.1 will be discussed independently in Section A.1 to A.6 of the paper. Each block shown in Fig. A.1 represents a set of calculations in Simulink® that calculates the parameter value that is stated on the block. The air temperature around the beans in the drum, indicated as environmental temperature in Fig. A.1., is directly linked to the burner's liquid petroleum gas (LPG) flow (F_{gas}). Initial experiments demonstrated a clear linear correlation between the LPG flow and the environmental temperature within the drum. When a step change was induced in the LPG flow to the burner, a linear change in the environmental air temperature was observed. As a result, the environmental air temperature was employed as a manipulated variable in the model in order to assess how the burner's LPG flow impacts the two controlled variables, $\dot{T}_{roast}$ and $\dot{T}_{roast}$.

A.1. Bean temperature subsystem

The bean temperature model equation is provided in the form of a dynamic energy balance in Eq. (A.1). It denotes the change in bean temperature (T_b) over time (t). F_g represents the flow of air through the system and Cp_g the heat capacity of the air; whereas, Cp_b represents the heat capacity of the roasted coffee beans. The inlet ($T_{g,i}$) and outlet ($T_{g,o}$) air temperature influence the energy balance greatly, as do the heat generated by the exothermic reactions (Q_r). The mass of the coffee beans ($m_{b(d.b)}$) was measured in their dry form, and the latent heat of vaporization is represented by ΔH_v, and the moisture content by X_b.

$$\frac{dT_b}{dt}=\frac{F_gCp_g\left[T_{g,i}-T_{g,o}\right]+m_{b(d.b)}\left(Q_r+\Delta H_v\frac{dX_b}{dt}\right)}{m_{b(d.b)}(1+X_b)Cp_b} \tag{A.1}$$

A.2. Moisture loss subsystem

A semi-empirical equation was used to model the moisture loss ($\frac{dX_b}{dt}$) of the beans during roasting. An Arrhenius type equation was assumed to govern the temperature dependency of the diffusion coefficient. This model predicts moisture content, which is provided by Eq. (A.2), and calculates the moisture loss over time as a function of bean temperature (T_b) and the equivalent sphere diameter of the coffee beans (d_b).

$$-\frac{dX_b}{dt}=\frac{4.32\times 10^9\bullet X_b^2}{\left(d_b\times 10^3\right)^2}exp\left[\frac{-9889}{T_b}\right] \tag{A.2}$$

A.3. Thermophysical properties of the drying air subsystem

The heat capacity (Cp_g), thermal conductivity (k_g), viscosity (μ_g), and ρ_g, the density of the air are functions of air temperature (T_g). These functions were combined to create the drying air subsystem's equations. The drying air refers to the air drawn through the system, which is heated by the gas flame and which meets the bean batch to transfer heat via convection.

$$Cp_g = 5.3091 \times 10^{-17}\left[T_g^6\right] - 4.1550 \times 10^{-13}\left[T_g^5\right] + 1.3621 \times 10^{-9}\left[T_g^4\right] - 2.3267 \times 10^{-6}\left[T_g^3\right] + 2.1034 \times 10^{-3}\left[T_g^2\right] - 7.2075 \times 10^{-1}\left[T_g\right] + 1.0839 \times 10^{-3} \tag{A.3}$$

$$k_g = 1.3819 \times 10^{-20}\left[T_g^6\right] - 9.1506 \times 10^{-17}\left[T_g^5\right] + 2.2342 \times 10^{-13}\left[T_g^4\right] - 2.2872 \times 10^{-10}\left[T_g^3\right] + 6.8867 \times 10^{-8}\left[T_g^2\right] + 8.0128 \times 10^{-5}\left[T_g\right] + 7.6694 \times 10^{-4} \tag{A.4}$$

$$\mu_g = 1.2184 \times 10^{-24}\left[T_g^6\right] - 8.1123 \times 10^{-21}\left[T_g^5\right] + 1.6089 \times 10^{-17}\left[T_g^4\right] + 1.1460 \times 10^{-15}\left[T_g^3\right] - 3.9733 \times 10^{-11}\left[T_g^2\right] + 7.1226 \times 10^{-8}\left[T_g\right] + 4.8855 \times 10^{-7} \tag{A.5}$$

$$\rho_g = 353.34 \times T_g^{-1.002} \tag{A.6}$$

A.4. Air energy balance subsystem

These equations model the air's temperature changes as it is drawn through the system. The average air temperature increase (85 °C) justifies adding an air energy balance to the process model. Eq. (A.7) is integrated between the entry and exit air temperature values within the Simulink® model.

$$-G_g Cp_g \frac{dT_g}{dZ} = he\left(\frac{dA_b}{dZ}\right)\left[T_g - T_b\right] \tag{A.7}$$

where

$$he = \frac{h}{1 + 0.3Bi} \tag{A.8}$$

G_g is the transfer function of the gas, which is derived from the thermophysical properties of the air, and *he* is the effective heat transfer coefficient as a function of the Biot number (Bi). A_b is the bean surface area and Z the Path length of gas flow across a bean.

A.5. Exothermic roasting reaction subsystem

This portion of the model represents the second phase of the roasting process, which comprises various chemical reactions that produce heat as a result of their exothermic nature. The beans' exothermic reactions release heat immediately after the drying phase concludes. The heat produced (Q_r) in this subsequent phase of the reaction is quantified by Eq. (A.9). *He* is the amount of heat produced throughout the roasting process, with *Het* being the total amount of heat produced during roasting. Table A.1 lists the relevant constants used in Eq. (A.9) and (A.10).

$$Q_r = Ar \bullet \exp\left[\frac{-\Delta E}{R(T_b)}\right]\left(\frac{Het - He}{Het}\right) \tag{A.9}$$

Eq. (A.10) is used to calculate accumulated heat generated at any given time.

$$He = \sum Q_r \bullet \Delta t \tag{A.10}$$

A.6. Roast profile subsystem

Finally, this equation uses input from the preceding subsystems to determine the final roast profile under the specified conditions. The roast profile constant (C) was determined to be 0.016 by Schwartzberg [6]. The output from this subsystem is used to calculate the derivative of the roast profile, which represents the rate of temperature change of the bean batch. T_{rp} is the roast profile temperature.

$$\frac{dT_{rp}}{dt} = C\left(T_b - T_{rp}\right) \tag{A.11}$$

$$\dot{T}_{roast} = \frac{d}{dt}\left(\frac{dT_{rp}}{dt}\right) = \frac{d}{dt}\left(C\left(T_b - T_{rp}\right)\right) \tag{A.12}$$

Table A.1
Constants used in Simulink® process model

Symbol	Description	Value of constant	Unit
Ar	Arrhenius equation prefactor.	$116\,200 \times 10^3$	W/kg
$\frac{\Delta E}{R}$	Activation energy divided by gas law constant.	5500	K
Het	Total amount of heat produced during roasting.	232×10^3	J/kg
ΔH_v	Latent heat of vaporization.	2790×10^3	J/kg

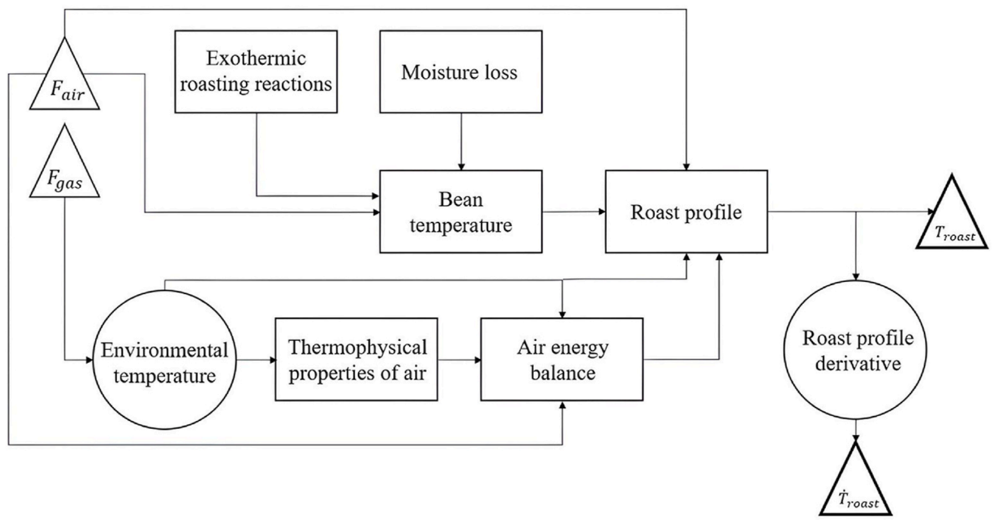

Fig. A.1. Subsection interaction within the Simulink® process model

Appendix B. Experimentally determined values used in controller design

Table B.1
Average dead time and process gradient values

Time of step change	Average dead time (θ)	Average gradient (K)
90 s	17.2 s	1.97×10^{-4} °C/s^2
240 s	20.4 s	3.48×10^{-4} °C/s^2
300 s	23.2 s	4.42×10^{-4} °C/s^2
Experimental average gradient	–	3.36×10^{-4} °C/s^2
Simulation average gradient	–	3.22×10^{-4} °C/s^2
Overall average gradient	–	3.29×10^{-4} °C/s^2

Table B.2
Experimental outputs used to determine overall average process gain

Prime temperature	Average change in process output due to step change	Average process gain (K_p)
170 °C	7.38×10^{-2} °C/s	1.48×10^{-3} °C/kg
180 °C	7.19×10^{-2} °C/s	1.44×10^{-3} °C/kg
200 °C	9.86×10^{-2} °C/s	1.97×10^{-3} °C/kg
210 °C	7.68×10^{-2} °C/s	1.54×10^{-3} °C/kg
230 °C	3.76×10^{-2} °C/s	7.52×10^{-4} °C/kg
Overall average process gain		1.43×10^{-3} °C/kg

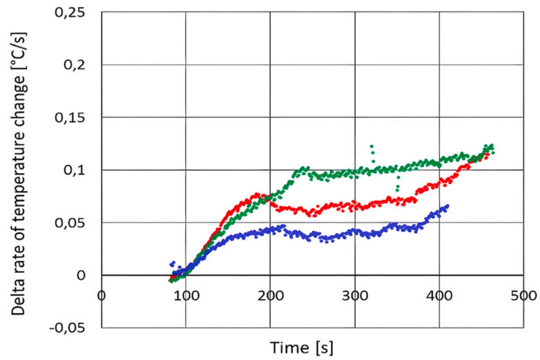

Fig. B.1. First-order plus time delay behavior of roasting process, step change induced at 90 s; 170 °C (●), 200 °C (●), 230 °C (●). Abbreviated title: A coffee roasting control strategy.

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