IMPROVING THE COTTONSEED OIL EXTRACTION SYSTEM USING AN ADAPTIVE CONTROL APPROACH

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Abstract. This paper addresses the automatic control of the pre-pressing heating stage in the process of oil extraction from cottonseed. The heating-chamber temperature is selected as the principal controlled variable, while variations in feedstock flow rate and moisture content are treated as disturbances. Since the properties of the raw material are unstable, a PID controller with fixed gains may lose performance when the operating point shifts. To overcome this, the plant is described by a discrete-time ARX model whose parameters are estimated online by the recursive least squares method with a forgetting factor, and the PID gains are updated on the basis of these estimates using bounded increments. In a 120-minute simulation, the adaptive controller was compared with a fixed-parameter controller: the integral absolute error decreased by 32.8 %, the integral squared error by 40.5 % and the root-mean-square error by 22.9 %. The reported figures are not plant measurements but simulation results obtained from a mathematical model; therefore, they must be validated under real production conditions.

Keywords: cottonseed; oil extraction; automatic control; adaptive control; ARX model; recursive least squares; PID controller; simulation.

СОВЕРШЕНСТВОВАНИЕ СИСТЕМЫ ПОЛУЧЕНИЯ МАСЛА ИЗ ХЛОПКОВЫХ СЕМЯН НА ОСНОВЕ АДАПТИВНОГО УПРАВЛЕНИЯ

Аннотация. В статье рассматривается задача автоматического управления стадией предпрессового нагрева в процессе получения масла из хлопковых семян. Температура греющей камеры принята основной регулируемой величиной, а изменения расхода и влажности сырья – возмущающими воздействиями. Поскольку свойства сырья нестабильны, ПИД-регулятор с постоянными коэффициентами может терять качество при смене рабочей точки. Для решения этой проблемы объект описан дискретной ARX-моделью, её параметры оцениваются в реальном времени рекурсивным методом наименьших квадратов с коэффициентом забывания, а коэффициенты ПИД-регулятора обновляются по этим оценкам с ограничением шага. В 120-минутной имитации адаптивный регулятор сопоставлен с регулятором с постоянными параметрами: интегральная абсолютная ошибка снизилась на 32,8 %, интегральная квадратичная – на 40,5 %, среднеквадратичная – на 22,9 %. Приведённые числа получены на математической модели, а не на заводских измерениях, поэтому требуют проверки в производственных условиях.

Ключевые слова: хлопковые семена; получение масла; автоматическое управление; адаптивное управление; ARX-модель; рекурсивный метод наименьших квадратов; ПИД-регулятор; имитационное моделирование.

PAXTA CHIGITIDAN YOG‘ OLISH TIZIMINI ADAPTIV BOSHQARUV USULI ASOSIDA TAKOMILLASHTIRISH

Annotatsiya. Maqolada paxta chigitidan yog‘ olish jarayonining presslashdan oldingi qizdirish bosqichini avtomatik boshqarish masalasi o‘rganilgan. Qizdirish kamerasi harorati asosiy rostlanuvchi kattalik sifatida tanlangan, xomashyo sarfi va namligining o‘zgarishi esa buzuvchi ta’sir deb qaralgan. Xomashyo xossalari beqaror bo‘lgani uchun doimiy koeffitsiyentli PID rostlagich ish nuqtasi o‘zgarganda sifatini yo‘qotishi mumkin. Buni bartaraf etish maqsadida obyekt diskret ARX modeli bilan tavsiflangan, uning parametrlari unutish koeffitsiyentli rekursiv eng kichik kvadratlar usuli bilan onlayn baholangan, PID koeffitsiyentlari esa shu baholar asosida chegaralangan qadamlar bilan yangilab borilgan. 120 daqiqalik simulyatsiyada adaptiv rostlagich doimiy parametrli rostlagich bilan taqqoslangan: integral absolyut xato 32,8 %, integral kvadratik xato 40,5 %, o‘rtacha kvadratik xato 22,9 % kamaygan. Keltirilgan raqamlar zavod o‘lchovlari emas, matematik model asosidagi simulyatsiya natijalaridir, shu sababli ular real ishlab chiqarish sharoitida tasdiqlanishi lozim.

Kalit so‘zlar: paxta chigiti; yog‘ olish; avtomatik boshqarish; adaptiv boshqaruv; ARX model; rekursiv eng kichik kvadratlar; PID rostlagich; simulyatsiya.

1. INTRODUCTION

Cottonseed is one of the main by-products of cotton ginning; it is processed into oil used for food and technical purposes, as well as into protein-rich oilcake (meal). The potential applications of cottonseed oil in the food, animal feed and biofuel sectors have been widely covered in the scientific literature [2].

Consequently, the stability of cottonseed processing and the oil yield have a direct impact on the efficiency of the cotton industry.

Mechanical oil extraction comprises feedstock preparation (cleaning and crushing), conditioning of moisture and temperature, and pressing. A review of oilseed expression has shown that oil recovery is jointly affected by pressure, temperature, pressing duration and feedstock moisture [1].

From a control standpoint, the difficulty lies in the fact that each input variable simultaneously affects both the oil yield and the product quality. Raising the temperature may improve the flowability of the material and facilitate oil release; however, excessive heating degrades product quality and increases energy consumption. When the moisture content changes, the optimal pressing regime shifts as well. As a result, a fixed-gain PID controller tuned at a single operating point may fail to ensure adequate performance in other regimes.

In adaptive control, the plant parameters are estimated during operation, and the controller gains are updated according to these estimates. This approach is well established in classical control theory under the name of self-tuning regulators [4, 5]; in the present work, it is applied to the pre-pressing heating stage of cottonseed.

The aim of the study is to develop an adaptive control structure that maintains a stable heating temperature and adapts to the operating regime when feedstock properties change, and to evaluate its effectiveness by means of a mathematical model and simulation.

Novelty of the work. A self-tuning PID scheme (online identification and gain updating with bounded increments) has been formulated as a unified control loop together with a simplified dynamic model of the cottonseed heating stage. It should be emphasised that the idea of adaptive PID control is not in itself new: the

contribution of this work lies in adapting it to a specific technological plant and in evaluating the results for that plant.

Theoretical and practical significance. From a theoretical perspective, the paper describes the application of a scheme comprising an ARX model, recursive least squares with a forgetting factor and bounded gain updating to the cottonseed heating plant. From a practical perspective, the proposed structure can be incorporated into existing PLC-based control systems with minor modifications; however, this requires prior verification against real measurements.

2. LITERATURE REVIEW

Studies devoted to the efficiency of oil expression from oilseeds mainly analyse the influence of process factors – pressure, temperature, moisture and feedstock pretreatment; the review by Khan and Hanna is one of the classic sources in this field [1]. Another review on cottonseed oil considered here focuses mainly on improving oil and protein content through genetic approaches [2]. In the sources reviewed, the relationship between process factors and oil yield is studied predominantly from a static perspective, whereas the dynamic properties of the control loop have not been addressed as a separate research problem.

PID is the most widely used controller in industrial processes, and methods for tuning its gains are described in detail in the monograph by Åström and Hägglund [3]. The gains are usually selected according to the plant dynamics at a particular operating point; if the plant gain or time constant changes, such tuning ceases to be optimal.

One approach to solving this problem is the self-tuning regulator. Åström and Wittenmark proposed a scheme that combines recursive estimation and controller synthesis within a single loop [4], and the theory of adaptive control was subsequently consolidated in a monograph [5]. Algorithms of digital self-tuning

controllers and issues of their practical implementation are presented in the book by Bobál et al. [6].

In the identification part, the ARX structure and the recursive least squares method are among the most commonly used tools [7]. For plants with time-varying parameters, a forgetting factor is introduced to reduce the weight of past measurements; a variable forgetting factor has also been employed in self-tuning regulators [8].

Thus, the process factors of mechanical pressing [1, 2], on the one hand, and the theory of adaptive control and identification [3–8], on the other, have been studied sufficiently. Within the scope of the sources reviewed by the authors, no study was found that combines these two lines of research for the pre-pressing heating stage of cottonseed on the basis of a control-oriented dynamic model. The present paper aims to fill this gap.

3. MATERIALS AND METHODS

3.1. Object of study and model

An oil extraction unit with a pre-pressing heating stage was selected as the object of study (Fig. 1). Temperature control at this stage was taken as the main loop, since temperature is a key parameter that determines the technological state of the feedstock. Pressing pressure and feedstock flow rate were accounted for in the model as disturbances.

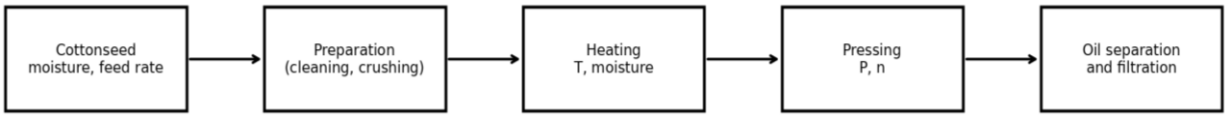

Fig. 1. Simplified control structure of the cottonseed oil extraction system.

The model was not intended to fully represent all physicochemical phenomena of the process; instead, a dynamic approximation sufficient for control system design was used. The heating chamber was represented as a first-order lag element:

$$\tau \, dT/dt + T(t) = K \, u(t) + K_z \, z(t) \quad (1)$$

where $T(t)$ is the chamber temperature, °C; $u(t)$ is the control signal corresponding to the heating power; $z(t)$ is the lumped effect of feedstock flow rate, moisture and heat losses; K is the gain of the control channel; K_z is the effective disturbance gain; τ is the time constant of the plant.

3.2. Discrete-time model

For digital control, the plant was described by an ARX model with a one-sample delay (two autoregressive and two input terms, i.e. $n_a=2$, $n_b=2$, $n_k=1$):

$$y(k) = -a_1 y(k-1) - a_2 y(k-2) + b_1 u(k-1) + b_2 u(k-2) + \varepsilon(k) \quad (2)$$

where $y(k)$ is the measured temperature; $u(k)$ is the control signal; $\varepsilon(k)$ is a random term representing measurement and modelling errors; a_1, a_2, b_1, b_2 are unknown, slowly time-varying parameters. It was assumed that differences in feedstock moisture, density and initial temperature cause these parameters to change slowly.

3.3. Online parameter estimation

The recursive least squares (RLS) method with a forgetting factor was chosen to estimate the parameters during operation. The parameter vector and the regressor vector are defined as follows:

$$\theta(k) = [a_1(k), a_2(k), b_1(k), b_2(k)]^T, \quad \varphi(k) = [-y(k-1), -y(k-2), u(k-1), u(k-2)]^T \quad (3)$$

The estimation equations are:

$$L(k) = P(k-1)\varphi(k) / [\lambda + \varphi^T(k) P(k-1) \varphi(k)] \quad (4)$$

$$\theta(k) = \theta(k-1) + L(k)[y(k) - \varphi^T(k)\theta(k-1)] \quad (5)$$

$$P(k) = [I - L(k)\varphi^T(k)]P(k-1)/\lambda \quad (6)$$

where $L(k)$ is the gain vector; $P(k)$ is the covariance matrix; λ is the forgetting factor, $0<\lambda\leq 1$. When λ is close to unity, the estimator suits slowly varying parameters; a smaller value places more weight on recent measurements and allows faster changes to be tracked, but at the cost of increased sensitivity to noise.

3.4. Adaptive PID controller

A PID control law was used in the control loop:

$$u(t) = K_p e(t) + K_i \int e(t)dt + K_d de(t)/dt \quad (7)$$

In the adaptive algorithm, K_p, K_i and K_d are not constant: they are recalculated according to the estimated plant parameters. To prevent abrupt jumps in the gains, a bounded-increment update was used:

$$K_j(k) = sat[K_j(k-1) + \gamma_j \Delta K_j(k)], \quad j \in \{p, i, d\} \quad (8)$$

where γ_j is the adaptation rate; $\Delta K_j(k)$ is the correction computed according to the tuning rule selected on the basis of the current estimated model parameters; $sat[\cdot]$ is the saturation operator that limits the value to the range between the permissible minimum and maximum. Such limiting reduces the risk of actuator saturation and adaptation instability.

3.5. Technological performance index

The oil yield is evaluated using the following ratio:

$$\eta_o = (m_o / m_s) \times 100\ \% \quad (9)$$

where η_o is the oil yield; m_o is the mass of extracted oil; m_s is the mass of processed cottonseed. The mass balance is written as follows:

$$m_s = m_o + m_c + m_l \quad (10)$$

where m_c is the mass of oilcake (meal); m_l denotes process losses. These relationships are not included in the control algorithm in the present work; they are provided as a basis for linking the quality index to the control loop in future work.

3.6. Simulation conditions and evaluation criteria

The simulation lasted 120 min, with an initial temperature of 65 °C. The setpoint *r(t)* was changed stepwise: 70 °C for 0–20 min, 75 °C for 20–60 min, 72 °C for 60–90 min and 78 °C for 90–120 min. Step changes in feedstock flow rate and heat loss were modelled as disturbances. A fixed-gain PID controller tuned at a single operating point was used for comparison. The control error was defined as:

$$e(t) = r(t) - T(t) \tag{11}$$

Control performance was evaluated using the integral absolute error (IAE), the integral squared error (ISE) and the root-mean-square error (RMSE); t_f is the simulation duration, N is the number of computation steps, and Δt is the step size:

$$IAE = \int |e(t)|dt \approx \Sigma |e(k)|\Delta t, \quad 0 \le t \le t_f \tag{12}$$

$$ISE = \int e^2(t)dt \approx \Sigma e^2(k)\Delta t, \quad 0 \le t \le t_f \tag{13}$$

$$RMSE = \sqrt{[(1/N)\ \Sigma e^2(k)]} \tag{14}$$

All figures reported in this paper are not measurements from a real unit but simulation data generated to demonstrate the method.

4. RESULTS

4.1. Setpoint tracking

Fig. 2 shows the setpoint and the output temperature of the adaptive system over the 120-minute simulation. Owing to thermal inertia, the temperature approaches the setpoint smoothly rather than instantaneously. For example, after the setpoint is raised to 75 °C at 20 min, the temperature settles near this value at approximately 50–55 min; when the setpoint is lowered to 72 °C at 60 min, it is

reached at approximately 80 min. In the last transition (90 min, 78 °C), the temperature reaches approximately 77.6 °C by 120 min and has not yet fully attained the setpoint. Such transient durations are typical of a plant with large thermal inertia and may reduce the risk of overloading the heating elements and of local overheating of the material.

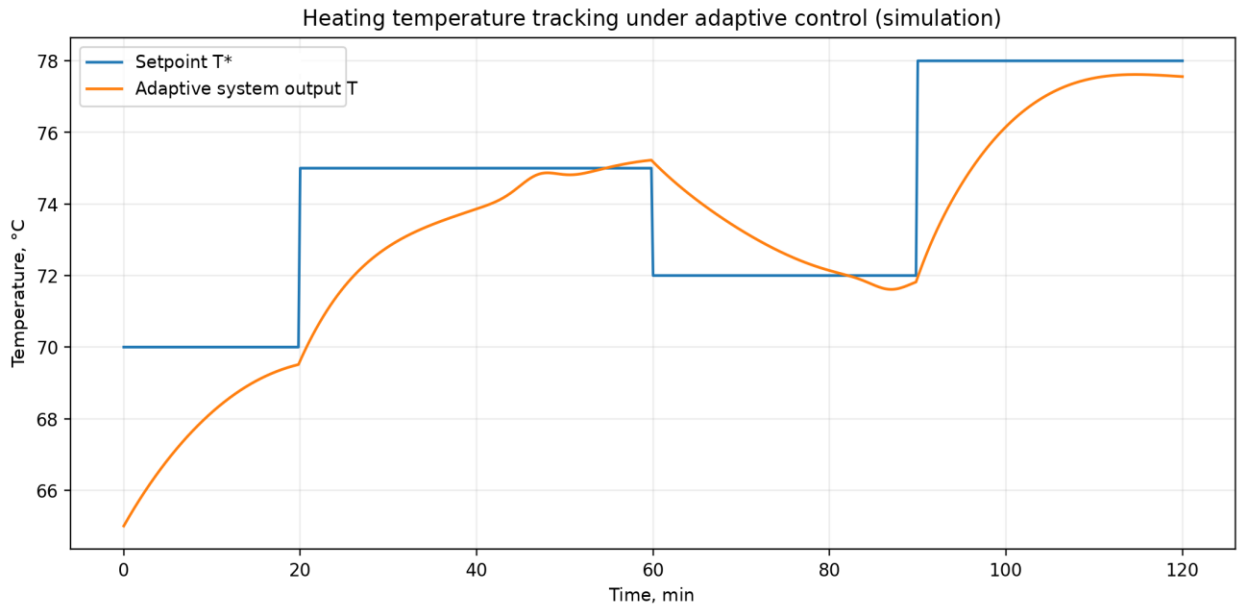

Fig. 2. Heating temperature setpoint tracking under adaptive control.

4.2. Comparison of fixed-gain and adaptive PID controllers

Fig. 3 presents the responses of the two systems. For the fixed-parameter PID, the gains were selected at a single operating point, whereas the adaptive PID continuously updated its gains on the basis of RLS identification. The fixed PID may perform well at the first operating point, but the transient response becomes prolonged when the plant gain or time constant changes. By recalculating its parameters, the adaptive PID partially compensates for this mismatch. This result is consistent with the primary purpose of adaptive control – adaptation to uncertain or time-varying parameters [4].

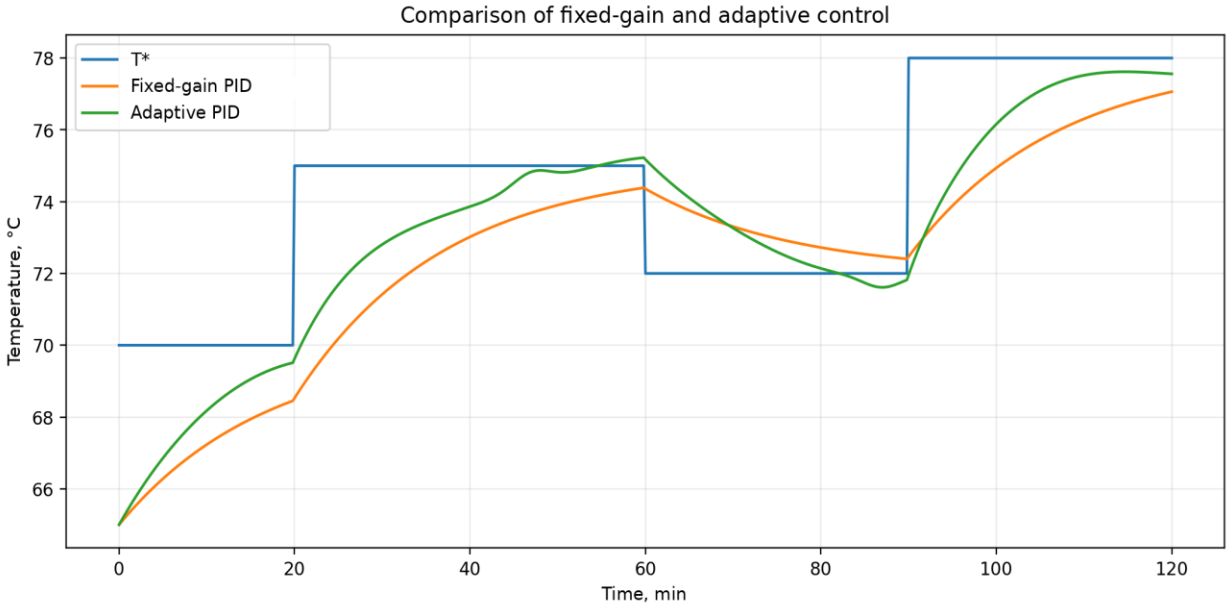

Fig. 3. Comparison of the responses of the fixed-parameter PID and the adaptive PID.

4.3. Effect of temperature and moisture on oil yield (model example)

To illustrate the interaction between temperature and moisture, a response surface was computed using a simplified empirical model. The model is not based on experimental data; therefore, the maximum point on the plot should be regarded not as a real technological optimum, but as a mathematical example illustrating the operating regime sought in the control problem. In general, oil release may be poor at low temperatures, while at high values the additional benefit diminishes and other technological constraints arise; it is also advisable to keep the moisture content within a certain range.

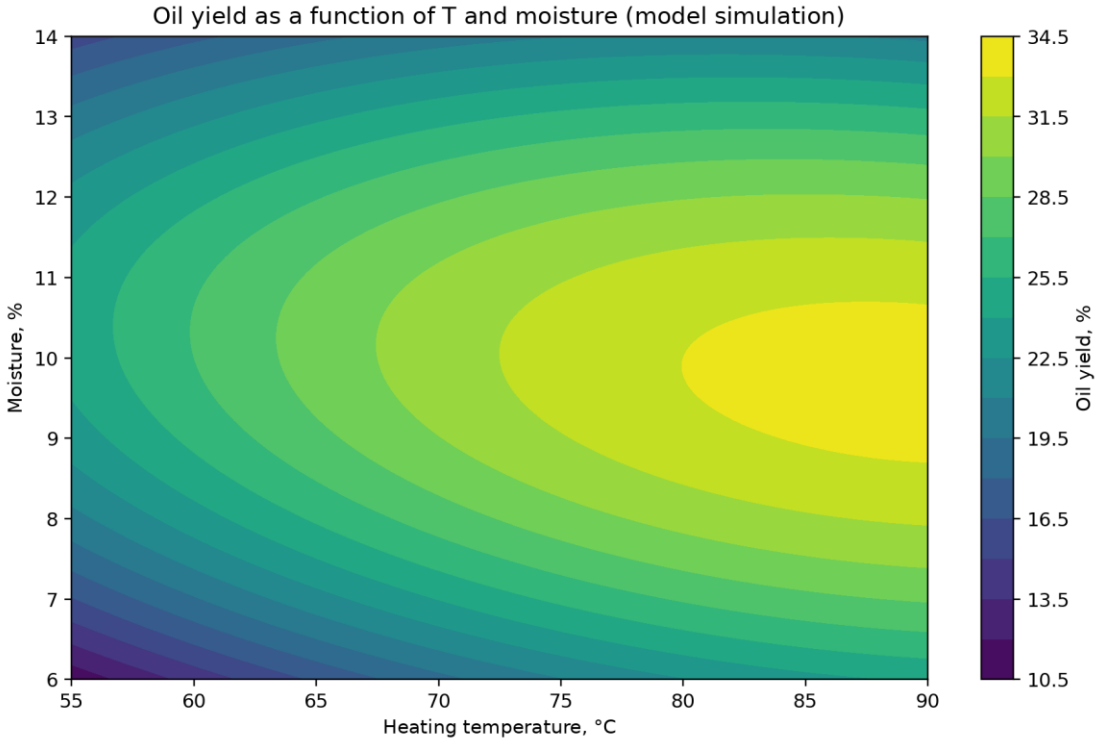

Fig. 4. Effect of temperature and moisture on oil yield: simplified model simulation.

4.4. Adaptation of controller parameters

Fig. 5 shows the time evolution of the adaptive PID gains (K_p and K_i are plotted; K_d is not shown). Over approximately the first 55 min, K_p decreases smoothly from 2.05 to about 1.81, while K_i decreases from 0.21 to about 0.17. At approximately 55 and 90 min, the gains change in a step-like manner (K_p first increases from 1.81 to 1.93 and then decreases from 1.92 to 1.84), reflecting changes in the plant parameters estimated through identification. In the subsequent intervals, the gains remain relatively stable. This demonstrates the interdependence of the identification and control loops in the adaptive system.

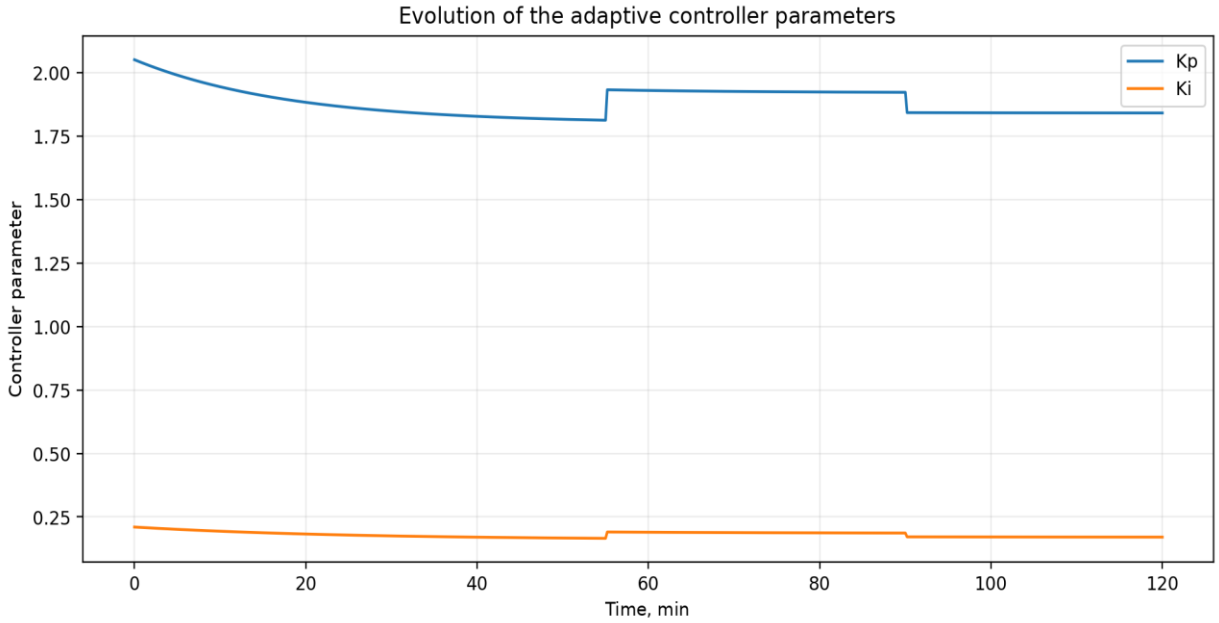

Fig. 5. Adaptation of the adaptive PID parameters during the simulation.

4.5. Control error and performance indices

The control errors are compared in Fig. 6, and the numerical IAE, ISE and RMSE values are given in Table 1. The adaptive control reduces the error more rapidly when switching to a new setpoint.

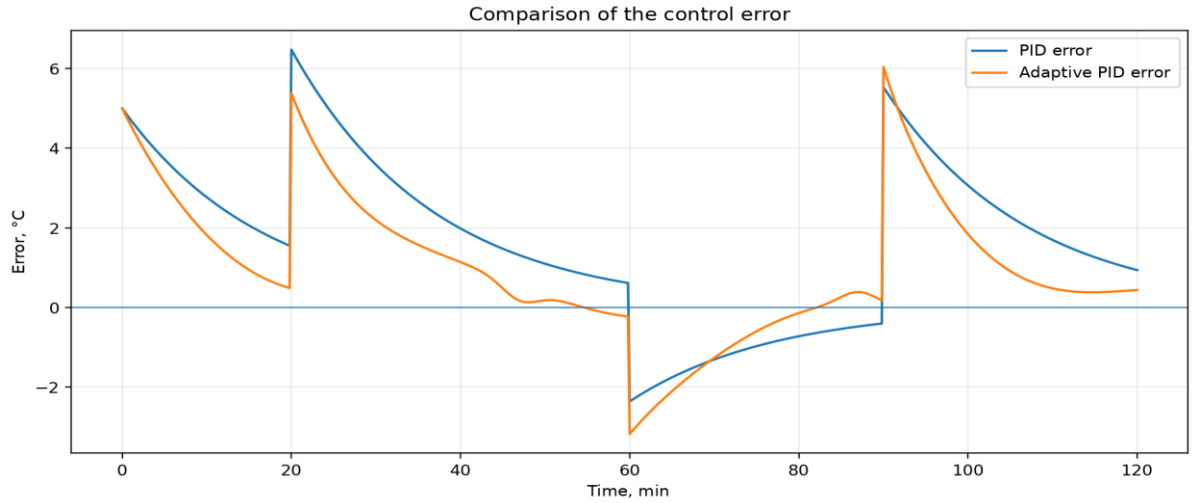

Fig. 6. Comparison of the temperature control error.

Table 1. Simulated control performance indices (illustrative results).

Criterion	Fixed PID	Adaptive PID	Change
IAE, °C·min	270.24	181.48	32.8 % reduction
ISE, °C²·min	849.04	505.14	40.5 % reduction
RMSE, °C	2.658	2.050	22.9 % reduction

According to the table, the adaptive PID reduced IAE by 32.8 %, ISE by 40.5 % and RMSE by 22.9 % compared with the fixed PID. The larger reduction in ISE is explained by the fact that the quadratic criterion places greater weight on large errors, and the adaptive controller shortens precisely the large deviations that occur during transients. The values in the table are simulated indices obtained by numerical computation from the plotted responses; they cannot be regarded as normative or experimental results for a real production line. For practical implementation, these criteria should be recalculated using real sensor data.

5. DISCUSSION

The simulation results indicate that the idea of applying adaptive control to the cottonseed heating stage is sound from an engineering standpoint: under model conditions, the adaptive controller reduced the error criteria by 23–41 %. At the same time, this conclusion relies solely on a mathematical model and must be confirmed for the real plant.

In a conventional feedback loop, the PID gains are selected once and remain unchanged over the entire operating range. If the plant dynamics depend on the operating point, a single tuning may produce an excessively sluggish response in some regimes and an excessively aggressive one in others. The adaptive approach,

by contrast, involves two levels: the first is the estimation of plant parameters, and the second is the retuning of the controller based on these estimates. In such a structure, identification must be sufficiently fast yet not overly sensitive to noise; otherwise, random fluctuations in the parameter estimates will induce oscillations in the control signal as well.

In this respect, the forgetting factor λ is an important tuning parameter. Values of λ close to unity are suitable for smoothly varying plants, whereas it can be reduced to adapt more quickly to new data when the process changes abruptly. However, if λ is too small, measurement noise propagates strongly into the model parameters. Therefore, in a practical system, λ should be selected on the basis of experimental identification and an analysis of the noise level.

Physical constraints must also be imposed on the control signal: the heating power must remain within $0 \le u \le u_{max}$, the press motor speed within $n_{min} \le n \le n_{max}$, and the process temperature within the safety limit $T \le T_{max}$. Therefore, rather than feeding the PID output directly to the actuator, the use of saturation and anti-windup mechanisms is recommended:

$$u_{lim}(k) = min\{u_{max}, max\{u_{min}, u(k)\}\} \quad (15)$$

A transition to multivariable control is also possible: in a MIMO system that simultaneously controls temperature, pressing pressure and feedstock flow rate, the coupling between channels is taken into account. For instance, an increase in flow rate raises the thermal load on the heating system, so the heating power must be increased to maintain the temperature. For such a problem, decoupling, model predictive control (MPC) or adaptive optimal control methods may be tested at a later stage.

Oil yield is not determined by temperature alone: in mechanical pressing, feedstock preparation, moisture, pressure and temperature jointly affect the outcome

[1]. Hence, in the future, oil yield and quality indices obtained from laboratory or online analysers could be fed into a higher-level optimisation loop.

A practical control architecture may consist of a PLC or industrial computer, temperature and pressure sensors, a flow meter, a frequency converter, an electric heater, a press motor and an operator interface. Fast PID loops operate at the lower level, while the identification and adaptation algorithm runs at the upper level; such a distributed structure meets real-time requirements while also enabling diagnostics and data archiving.

Limitations of the study. First, all results were obtained in a single simulation scenario and have not been validated with real sensor data. Second, if the plant in the simulation was chosen with a structure close to the identification model, the results may be optimistic relative to real conditions. Third, the response surface in Fig. 4 is based on an illustrative rather than an experimental model. Therefore, future work should verify the model against real measurements and conduct repeated simulations with varying noise levels and initial conditions.

6. CONCLUSIONS

1. The heating stage of cottonseed oil extraction was represented as a first-order dynamic plant and, for digital control, as an ARX model. An adaptive controller structure was developed that estimates the plant parameters online using recursive least squares with a forgetting factor and updates the PID gains with bounded increments on the basis of these estimates.

2. In a 120-minute simulation, the adaptive PID reduced the integral absolute error by 32.8 %, the integral squared error by 40.5 % and the root-mean-square error by 22.9 % compared with the fixed-parameter PID. These results indicate that the adaptive approach is promising under changing operating regimes.

3. Since the figures were obtained from a simulation based on a mathematical model, they must be validated in real production. As a first step, it is necessary to collect real-time series from the production line, determine the operating range of the plant, assess sensor accuracy and verify the identification model against experimental data.

4. At the next stage, it is advisable to develop a multi-loop (MIMO) adaptive system that controls moisture, pressure and feedstock flow rate in addition to temperature, and to link it to oil yield and quality indices.

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