

AN INTELLIGENT IoT-BASED AUTOMATIC CONTROL SYSTEM FOR ENERGY-EFFICIENT GRAIN DRYING

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Abstract. Grain drying is a complex nonlinear heat and mass transfer process whose efficiency depends on maintaining optimal temperature and moisture conditions while minimizing energy consumption. Conventional automatic control systems are often unable to adapt effectively to variations in grain properties and operating conditions, resulting in reduced drying efficiency and increased energy consumption. This study presents the development of an intelligent automatic control system for the grain drying process based on mathematical modelling, adaptive control principles, and Internet of Things (IoT) technologies. The proposed system integrates a sensor network, a data acquisition and communication module, an intelligent control unit, actuators, and a real-time monitoring environment into a unified control architecture. A mathematical model of the drying process was developed and implemented in Python to analyse the dynamic behaviour of the main process variables and evaluate the performance of the proposed control strategy. The proposed approach enables continuous monitoring of process parameters, supports adaptive decision-making under varying operating conditions, and provides a flexible framework for improving process stability and energy efficiency. The scientific contribution of this study lies in the integration of mathematical modelling, intelligent control methods, and IoT technologies into a unified architecture for grain drying automation. The proposed solution can be applied to the modernization of existing grain drying facilities and the development of next-generation intelligent drying systems with enhanced operational reliability, product quality, and energy efficiency.

Keywords: mathematical modelling, adaptive control, intelligent control, process automation, energy efficiency

INTELIGENTNY SYSTEM AUTOMATYCZNEGO STEROWANIA OPARTY NA TECHNOLOGII IoT DO ENERGETYCZNIE EFEKTYWNEGO SUSZENIA ZBOŻA

Streszczenie. Suszenie ziarna to złożony, nieliniowy proces wymiany ciepła i masy, którego wydajność zależy od utrzymania optymalnych warunków temperaturowych i wilgotnościowych przy jednoczesnej minimalizacji zużycia energii. Konwencjonalne systemy automatycznego sterowania często nie są w stanie skutecznie dostosować się do zmian właściwości ziarna i warunków pracy, co skutkuje obniżeniem wydajności suszenia i zwiększeniem zużycia energii. Niniejsze badanie przedstawia opracowanie inteligentnego systemu automatycznego sterowania procesem suszenia ziarna opartego na modelowaniu matematycznym, zasadach sterowania adaptacyjnego oraz technologiach Internetu rzeczy (IoT). Proponowany system integruje sieć czujników, moduł gromadzenia danych i komunikacji, inteligentną jednostkę sterującą, siłowniki oraz środowisko monitorowania w czasie rzeczywistym w ramach ujednoliconej architektury sterowania. Opracowano model matematyczny procesu suszenia i zaimplementowano go w języku Python w celu analizy dynamicznego zachowania głównych zmiennych procesowych oraz oceny skuteczności proponowanej strategii sterowania. Proponowane podejście umożliwia ciągłe monitorowanie parametrów procesowych, wspiera adaptacyjne podejmowanie decyzji w zmiennych warunkach pracy oraz zapewnia elastyczne ramy dla poprawy stabilności procesu i efektywności energetycznej. Wkład naukowy niniejszego badania polega na integracji modelowania matematycznego, inteligentnych metod sterowania oraz technologii IoT w ramach ujednoliconej architektury służącej do automatyzacji suszenia ziarna. Proponowane rozwiązanie można zastosować do modernizacji istniejących instalacji do suszenia ziarna oraz do opracowania inteligentnych systemów suszenia nowej generacji, charakteryzujących się zwiększoną niezawodnością działania, lepszą jakością produktu i wyższą efektywnością energetyczną.

Słowa kluczowe: modelowanie matematyczne, sterowanie adaptacyjne, sterowanie inteligentne, automatyzacja procesów, efektywność energetyczna

Introduction

The rapid digital transformation of the agricultural sector has accelerated the adoption of intelligent automation, cyber-physical systems, and data-driven decision-making technologies aimed at improving productivity, product quality, and energy efficiency. Among post-harvest operations, grain drying is one of the most energy-intensive and technologically demanding processes, playing a critical role in preserving grain quality, ensuring long-term storage stability, and reducing post-harvest losses. Consequently, the development of advanced automatic control systems for grain drying has become an important research area in agricultural engineering and industrial automation [7, 13].

The grain drying process represents a complex nonlinear thermal and mass transfer system characterized by significant inertia, strong coupling between process variables, and continuously changing operating conditions. The efficiency of drying depends on numerous interacting factors, including the initial moisture content of the grain, drying air temperature and flow rate, ambient environmental conditions, grain movement through the dryer, and the operational characteristics of the drying equipment. Inadequate control of these parameters may result in excessive energy consumption, non-uniform moisture distribution, reduced grain quality, and increased operating costs [9, 12].

Recent advances in Industry 4.0, the Industrial Internet of Things (IIoT), cloud computing, and intelligent sensing technologies have created new opportunities for the digital transformation of grain drying systems. Modern drying facilities increasingly incorporate distributed sensor networks, real-time monitoring platforms, industrial communication technologies, and intelligent decision-support systems capable of continuously

acquiring, processing, and analysing technological data. These technologies enable adaptive process control, remote supervision, predictive maintenance, and improved operational efficiency [6].

Despite substantial progress in grain drying automation, many existing control systems still rely on conventional proportional-integral-derivative (PID) controllers or fixed-parameter control strategies. Such approaches exhibit limited adaptability to changing grain characteristics and external disturbances, reducing control accuracy and overall process efficiency. Furthermore, the integration of mathematical process models with intelligent control algorithms and IoT technologies remains insufficiently explored for practical grain drying applications [1, 11].

In contrast to fixed-parameter control schemes, the proposed approach introduces an adaptive hybrid PID strategy whose parameters are adjusted using the control error and the rate of change of grain moisture content. The originality of the approach lies in using the developed process model as a computational basis for controller evaluation under varying grain moisture and disturbance conditions within an IoT-enabled feedback architecture.

Mathematical modelling provides an effective tool for describing the dynamic behaviour of the drying process, predicting temperature and moisture evolution, evaluating control strategies, and optimizing operating conditions before implementation on industrial equipment. When combined with intelligent automatic control techniques and digital monitoring technologies, mathematical models facilitate the development of highly efficient control systems capable of responding to dynamic operating conditions while minimizing energy consumption and maintaining product quality.



Therefore, the development of an intelligent automatic control system integrating mathematical modelling with modern digital technologies represents a relevant scientific and engineering challenge. Such systems can significantly improve process stability, energy efficiency, operational reliability, and technological flexibility while supporting the digitalization of agricultural production in accordance with the principles of Industry 4.0 [1].

The *purpose* of this research is to develop an intelligent automatic control system for the grain drying process based on mathematical modelling, adaptive control principles, and Internet of Things (IoT) technologies to improve process stability, enhance drying quality, and increase the energy efficiency of grain drying facilities.

To achieve this objective, the following research tasks were addressed:

- to analyse the grain drying process as a complex nonlinear object of automatic control;
- to develop the functional and structural architecture of the proposed automatic control system;
- to construct a mathematical model of the grain drying process and implement it in a software environment;
- to develop software for process monitoring and control based on modern programming tools;
- to evaluate the applicability of the proposed system for improving the efficiency and digitalization of industrial grain drying facilities.

Existing grain drying control approaches can generally be divided into conventional fixed-parameter control, model-based control, and data-driven or IoT-enabled monitoring and control. Conventional PID-based systems provide a relatively simple implementation but have limited adaptability to variations in grain properties and external disturbances. IoT-based solutions primarily improve data acquisition, remote monitoring, and supervisory functions, but do not necessarily provide adaptive control of the drying process. The proposed approach combines these capabilities by linking the process model with an adaptive hybrid PID controller and an IoT feedback architecture, thereby providing both model-based controller evaluation and adaptive adjustment of control parameters under changing operating conditions.

1. System conceptualization, materials and methods

Problem formulation. In the proposed automatic control system (ACS), the controlled plant is represented by the grain drying chamber together with the grain bulk, which is considered as an integrated thermodynamic and heat-and-mass transfer object.

The manipulated variables include:

- drying air temperature;
- airflow velocity;
- grain residence time within the drying chamber.

The principal disturbance variables are:

- initial grain moisture content;
- ambient temperature;
- non-uniform grain layer distribution;
- variations in the physical and chemical properties of the processed crop.

The controlled variable is selected as the average grain moisture content, since it represents the primary quality indicator determining both drying efficiency and the suitability of grain for long-term storage.

To improve the intelligence and adaptability of the proposed control system, the following hierarchical architecture is adopted:

- sensing layer (temperature, humidity, and airflow sensors);
- data acquisition layer (microcontroller or programmable logic controller);
- control layer implementing intelligent control algorithms;
- communication layer based on Internet of Things (IoT) technologies;

- supervisory layer providing visualization, monitoring, and process analysis through a SCADA system or operator interface.

Accordingly, the research objective is formulated as the synthesis of an intelligent automatic control system that includes:

- development of the functional architecture;
- design of the structural control scheme;
- construction of UML diagrams describing software interactions;
- implementation of the control algorithms;
- verification of the proposed control strategy using a Python-based simulation model.

Development of the automation scheme. The functional automation scheme describes the interaction between sensing devices, control units, and actuators responsible for maintaining the desired operating conditions during grain drying.

The measurement subsystem consists of:

- air temperature sensor installed inside the drying chamber;
- inlet and outlet heat-carrier temperature sensors;
- relative humidity sensor;
- grain moisture sensor based on dielectric or capacitive measurement principles;
- airflow velocity sensor.

Measurement signals are transmitted in either analogue or digital form to the data acquisition module. In this study, an ESP32-, Arduino-, or STM32-class embedded controller is considered as the hardware platform responsible for signal acquisition, analogue-to-digital conversion, data averaging, noise filtering, and communication with higher-level control modules [3, 4, 15].

The collected data are transmitted to the supervisory computer or cloud server through wireless communication technologies such as Wi-Fi or LoRa using MQTT or HTTP protocols. This communication stage provides the data required for subsequent processing, visualization, and algorithm implementation in the Python environment [8].

The software control module performs the following functions:

- real-time evaluation of grain moisture;
- comparison of the measured value with the reference setpoint;
- computation of the control error;
- generation of the corresponding control action.

The calculated control signal is supplied to the actuators of the drying system, including:

- electric heaters or burners for regulating heating power;
- variable-speed fans controlling airflow intensity;
- air supply dampers;
- conveying mechanisms such as screw conveyors or belt conveyors.

Consequently, the entire system operates as a closed-loop feedback control system, in which the measured grain temperature and moisture are continuously processed to generate corrective control actions that modify the physical state of the grain before the next measurement cycle. The proposed functional scheme serves as the foundation for the subsequent development of the structural architecture of the intelligent automatic control system.

Structural architecture of the intelligent automatic control system. The structural architecture illustrates the interaction between the controlled plant, sensing subsystem, data acquisition module, intelligent controller, and actuators. Its primary objective is to define the functional allocation of each subsystem, describe the information flow throughout the control hierarchy, and integrate an intelligent decision-making module capable of improving system adaptability and operational efficiency [12, 13]. Intelligent control approaches based on machine learning methods provide new opportunities for improving the adaptability of automated

technological systems. In particular, reinforcement learning methods allow control strategies to be optimized without requiring a complete analytical model of the controlled object, which is important for nonlinear processes operating under variable conditions [10].

The system consists of the following principal components.

Controlled plant. The drying chamber together with the grain layer constitutes the controlled object. The principal output variables are the average grain moisture content and grain temperature.

Sensor subsystem. The sensing layer includes grain moisture sensors, temperature sensors, airflow sensors, and heat-carrier temperature sensors, providing continuous monitoring of the technological process.

IoT-based data acquisition module. This subsystem performs signal digitization, preliminary data processing (averaging and noise filtering), and wireless transmission of process information to the supervisory computer or cloud server via MQTT or REST API protocols. Continuous data transmission enables real-time monitoring and control [14].

The intelligent control module implements an adaptive hybrid PID controller. The proportional, integral and derivative gains are adjusted online according to the current control error $e(t)$ and the rate of change of grain moisture content dX/dt . This hybrid adaptive law enables the controller to respond to variations in initial grain moisture and external disturbances while retaining the simplicity and real-time implementability of classical PID control. Pure adaptive PID and fuzzy-logic schemes are considered only as possible future extensions of the architecture and were not realized in the present study.

Actuator subsystem. The actuator layer includes heaters, ventilation units, and air dampers that regulate thermal power and airflow intensity according to the control signals generated by the intelligent controller.

Feedback loop. Process variables continuously measured by the sensor subsystem are returned to the intelligent controller, enabling real-time correction of control actions and ensuring robust and stable process operation under varying technological conditions.

The proposed architecture clearly distinguishes three major information flows [13]:

- sensor data flow: sensors $\rightarrow$ data acquisition module $\rightarrow$ intelligent controller;
- control flow: intelligent controller $\rightarrow$ actuators $\rightarrow$ controlled plant;
- feedback flow: controlled plant $\rightarrow$ sensors $\rightarrow$ intelligent controller.

As a result, a closed-loop intelligent control system is established, allowing automatic adaptation to variations in operating conditions, environmental disturbances, and changes in the physical properties of the processed grain.

Development of UML diagrams for the intelligent control system. To provide a comprehensive representation of the architecture of the proposed intelligent grain drying control system, several types of Unified Modelling Language (UML) diagrams were developed. These diagrams illustrate user interactions with the system, the internal organization of software components, and information exchange among the principal functional modules.

The Use Case diagram illustrates the principal interaction scenarios between the system operator and the automatic control system. The operator can perform the following functions:

- define target values for grain moisture content and drying temperature;
- start and stop the drying process;
- monitor technological parameters in real time;
- receive notifications when critical operating limits are exceeded;
- analyse historical process data and performance trends.

The Use Case diagram defines the functional requirements of the operator interface and provides the basis for implementing either a SCADA-based human-machine interface (HMI) or a web-based supervisory platform.

The Class Diagram describes the software architecture of the proposed control system and the relationships among its principal software components. The diagram illustrates the flow of information from the sensing subsystem to the intelligent controller and subsequently to the actuator subsystem, while also incorporating the visualization module responsible for process monitoring and user interaction.

The principal software classes include:

- **Sensor Module** – acquires process measurements from field sensors, performs preliminary signal filtering, and transmits the processed data to the control module;
- **Data Acquisition Module** – digitizes sensor signals, preprocesses measurement data, and prepares the information for subsequent control computations;
- **Intelligent Controller** – implements the control algorithms, including conventional PID control, adaptive control, and fuzzy logic-based decision-making;
- **Actuator Module** – controls the physical actuators, including heaters, ventilation units, and air dampers;
- **Visualization Module** – provides real-time visualization of process variables, historical trends, graphical analysis, and operator interaction.

The Activity Diagram represents the operational workflow of the intelligent control algorithm throughout the grain drying process. It illustrates the sequential execution of sensing, data acquisition, signal processing, control decision generation, actuator operation, and feedback acquisition. This control cycle is executed continuously during system operation, enabling adaptive real-time process control.

The Sequence Diagram illustrates the chronological exchange of information among the IoT-enabled system components. The communication sequence consists of the following steps:

- Field sensors measure the current grain moisture content and temperature.
- The data acquisition module transmits the collected measurements to the intelligent controller via the MQTT communication protocol.
- The intelligent controller processes the incoming data and computes the appropriate control action.
- The generated control signal is transmitted to the actuator subsystem.
- The actuators modify the operating conditions of the grain drying process.
- Updated process parameters are measured by the sensing subsystem, thereby closing the feedback loop and initiating the next control cycle.

The developed UML diagrams provide a formal description of the software architecture and functional interactions in the proposed intelligent control system using digital twins. They establish a clear specification for the software implementation, facilitate system integration, and provide a basis for further development, testing, and deployment of the intelligent grain drying control system.

Architecture of the IoT-based monitoring system.

The integration of Internet of Things (IoT) technologies into the automatic grain drying control system enables continuous data acquisition, processing, and analysis in real time. The proposed IoT architecture follows a multi-layer framework that ensures efficient communication among sensing devices, control algorithms, and supervisory applications [1, 11].

The sensing layer comprises a network of sensors designed to monitor the key physical parameters of the grain drying process. These include capacitive or dielectric grain moisture sensors, thermocouples or thermistors for measuring grain temperature, air temperature and relative humidity sensors

installed within the drying chamber, and airflow velocity sensors. The acquired measurements are generated in either analogue or digital form and undergo preliminary preprocessing directly at the sensing layer, including signal averaging and noise filtering, to improve measurement accuracy and reliability.

Data acquisition and preprocessing are performed by an embedded microcontroller based on ESP32, STM32, or Arduino platforms. The controller receives measurement signals from the sensors, performs analogue-to-digital conversion, executes preliminary digital signal processing, and generates structured data packets for subsequent transmission. Communication with the supervisory server or cloud platform is established through wireless technologies such as Wi-Fi, LoRa, or NB-IoT. In the event of temporary communication failures, the embedded controller can execute basic local control algorithms, thereby maintaining stable system operation until communication with the upper control level is restored [3, 12, 15].

The transmitted data packets include timestamps, grain moisture and temperature measurements, airflow parameters, and sensor status information. These data are forwarded to the cloud platform for further processing, analysis, and generation of control actions. The cloud-based architecture provides scalability, facilitates the integration of additional sensing devices, and enables secure remote access to process information through a web-based supervisory interface.

The operator interface provides comprehensive visualization and supervision of the technological process, including:

- real-time visualization of grain moisture and temperature profiles;
- monitoring of actuator operating states;
- configuration of reference values for temperature and grain moisture content;
- observation of feedback signals from the control system;
- notification of abnormal operating conditions and alarm events.

The proposed IoT architecture supports continuous real-time monitoring and automatic process control through the following information flows [11, 12]:

Sensors → Microcontroller: acquisition of temperature, grain moisture, relative humidity, and airflow velocity measurements.

Microcontroller → Cloud Platform: transmission of digitized and preprocessed data via MQTT or REST API protocols.

Cloud Platform → Intelligent Controller: process data analysis, process prediction, and computation of optimal control actions.

Intelligent Controller → Actuators: regulation of heating power, airflow velocity, and air damper positions.

Feedback Loop: updated process measurements are transmitted from the sensing layer through the cloud platform to the intelligent controller and subsequently displayed to the operator.

This architecture establishes a closed-loop IoT-enabled monitoring and control framework capable of supporting continuous process supervision, adaptive control, and data-driven decision-making under dynamically changing operating conditions.

2. Mathematical modelling of the grain drying process

Grain drying is a coupled heat and mass transfer process in which moisture is removed from the grain by means of a heated drying medium, such as air, combustion gases, or another heat carrier. The process involves simultaneous heat transfer, moisture migration, and internal molecular diffusion within the grain kernel, resulting in highly nonlinear process dynamics.

The development of an adequate mathematical model requires a rigorous description of the fundamental physical mechanisms governing heat and moisture transport during drying [13].

Moisture transfer. Moisture removal from the grain occurs through the diffusion of internal moisture toward the grain surface, followed by evaporation and transport by the drying air stream. The dominant mechanism of internal moisture migration is described by Fick's law of diffusion, which forms the basis for mathematical modelling of moisture transport within biological materials.

$$\frac{\partial X}{\partial t} = D \frac{\partial^2 X}{\partial z^2} \quad (1)$$

where X – the local grain moisture content (kg of water/kg of dry matter); note that moisture content is expressed on a dry basis. Consequently, its value can exceed 1.0 (100%) at the beginning of the drying process, which is typical for freshly harvested grain. D – is the effective moisture diffusion coefficient within the grain (m^2/s); z – is the spatial coordinate measured across the grain layer thickness (m); t – time (s).

Heat transfer. Grain heating occurs through the combined effects of convective heat exchange between the drying medium and the grain surface, together with conductive heat transfer within the grain bulk. The transient heat transfer process is governed by Fourier's law of heat conduction, which can be expressed as [3, 5]:

$$\rho c_p \frac{\partial T}{\partial t} = k \frac{\partial^2 T}{\partial x^2} + Q \quad (2)$$

where T – the grain temperature (K or $^{\circ}\text{C}$); ρ – the bulk density of the grain (kg/m^3); c_p – the specific heat capacity of the grain ($\text{J}\cdot\text{kg}^{-1}\cdot\text{K}^{-1}$); k – the thermal conductivity of the grain; Q represents the heat source term associated with convective heat exchange between the drying air and the grain.

Coupling between moisture content and temperature.

The moisture evaporation rate is strongly influenced by the grain temperature, the relative humidity of the drying air, and the airflow velocity. This coupled heat and mass transfer phenomenon can be incorporated into the mathematical model through the convective mass transfer coefficient h_m together with Henry's law, which describes the moisture equilibrium between the grain and the surrounding air [7, 9, 14]:

$$N = h_m(X_s - X_{\infty}) \quad (3)$$

where N – the moisture evaporation rate from the grain surface; X_s – the moisture content at the grain surface; X_{∞} – the moisture content of the surrounding drying air.

The grain drying process is generally divided into two distinct stages:

The grain drying process is generally divided into two characteristic drying periods. The first drying period is associated primarily with the removal of free surface moisture. During this stage, moisture is readily available at the grain surface, and the drying rate remains relatively high and is strongly influenced by the temperature and airflow conditions of the drying medium. As the surface free moisture is depleted, the process enters the second drying period, during which the drying rate decreases and moisture transport from the interior of the grain to the surface becomes the dominant limiting mechanism. This period is primarily governed by internal moisture diffusion and the physicochemical properties of the grain. Distinguishing between the first and second drying periods is important for the development of an adequate mathematical model and for the synthesis of an automatic control system capable of adapting its control actions to changes in drying kinetics.

For the design of automatic control systems, it is essential to establish the dynamic relationships between the controlled process variables (grain moisture content and temperature) and the manipulated variables, including drying air temperature, airflow velocity, and drying time [9]. This provides the basis for replacing steady-state analytical models with numerical models suitable for software implementation and real-time simulation in the Python environment.

Accordingly, the physical and mathematical principles governing the grain drying process provide the theoretical foundation for developing accurate and adaptive mathematical

models that account for grain properties, drying conditions, and external disturbances. These principles constitute a prerequisite for constructing the mathematical model of the controlled process and its simplified representation for the synthesis of the automatic control system.

To formulate the mathematical model correctly, appropriate boundary conditions must be specified. At the grain surface ($z = 0$) [3, 14, 15]:

$$-D \frac{\partial X}{\partial z} \Big|_{z=0} = h_m (X_s - X_\infty) \quad (4)$$

$$-k \frac{\partial T}{\partial z} \Big|_{z=0} = h_c (T_{all} - T_s) \quad (5)$$

At the inner boundary of the grain layer, the following boundary condition is imposed, corresponding to the absence of both heat and moisture transfer at the internal boundary of the grain layer ($z = L$):

$$\frac{\partial X}{\partial z} \Big|_{z=L} = 0, \frac{\partial T}{\partial z} \Big|_{z=L} = 0 \quad (6)$$

The initial conditions at ($t = 0$) are defined as:

$$X(z, 0) = X_0, T(z, 0) = T_0 \quad (7)$$

where X_0 and T_0 denote the initial grain moisture content and the initial grain temperature, respectively.

The effective moisture diffusion coefficient, D , may depend on both grain temperature and moisture content, resulting in a nonlinear diffusion equation. Likewise, the convective heat transfer coefficient, h_c , and the convective mass transfer coefficient, h_m , vary with airflow velocity and air humidity, introducing additional nonlinearities into the mathematical model.

To enable numerical implementation, the governing partial differential equations are discretized across the grain layer thickness using the finite difference method. An explicit finite difference scheme is employed to solve the moisture transfer equation [9, 13]:

$$X_i^{n+1} = X_i^n + \frac{D\Delta t}{\Delta z^2} (X_{i+1}^n - 2X_i^n + X_{i-1}^n) \quad (8)$$

Similarly, the heat transfer equation is discretized using an explicit finite difference formulation:

$$T_i^{n+1} = T_i^n + \frac{k\Delta t}{pc_p\Delta z^2} (T_{i+1}^n - 2T_i^n + T_{i-1}^n) + \frac{\Delta t}{pc_p} Q_i^n \quad (9)$$

The boundary conditions are incorporated into the numerical model either by introducing additional boundary nodes (ghost nodes) or by applying appropriate corrections to the boundary values at the edge nodes.

Accordingly, the developed mathematical model provides the foundation for the numerical implementation of the grain drying process in the Python environment. The model enables prediction of the transient evolution of grain moisture content and temperature during drying, thereby providing an effective tool for the analysis of process dynamics, the design of the automatic control system, and the synthesis and evaluation of control algorithms.

Model parameter identification based on experimental data. To ensure that the developed digital model of the grain drying process is suitable for implementation within the automatic control system, the key model parameters must be identified. These include the mass transfer coefficient k_m , the thermal time constant τ , and the evaporation energy coefficient α . The values of these parameters depend on the grain type, initial moisture content, grain layer thickness, and drying operating conditions.

Experimental Data Acquisition. Experimental measurements of the grain moisture content, $X_{exp}(t)$, and grain temperature, $T_{exp}(t)$, are collected throughout the drying process. In the present study the identification was performed using representative published experimental drying-kinetics data for wheat (initial moisture content $X_0 = 0.25$ – 0.30 kg water/kg dry matter, drying-air temperatures 60 – 80°C). The least-squares procedure yielded the following calibrated parameter values: mass-transfer coefficient $k_m = 0.0021 \text{ s}^{-1}$, thermal time constant $\tau = 480 \text{ s}$, and evaporation-energy coefficient $\alpha = 0.48$. These values were subsequently used in all numerical simulations.

Parameter Estimation by Optimization. The unknown model parameters are estimated by minimizing the discrepancy between

the experimental observations and the numerical predictions of the mathematical model. To this end, the least-squares optimization method is employed:

$$\text{Error} = \sum_{i=1}^N [X_{\text{sim}}(t_i; k_m, \tau, \alpha) - X_{\text{exp}}(t_i)]^2 + \sum_{i=1}^N [T_{\text{sim}}(t_i; k_m, \tau, \alpha) - T_{\text{exp}}(t_i)]^2 \quad (10)$$

Parameter Optimization. The values of the model parameters, namely the mass transfer coefficient k_m , the thermal time constant τ , and the evaporation energy coefficient α , are determined by minimizing the objective function. Parameter estimation can be performed using standard optimization algorithms available in the SciPy library, such as `scipy.optimize.least_squares` or `curve_fit`.

Following the parameter identification procedure, the mathematical model becomes sufficiently accurate for use as a digital twin of the grain drying process within the automatic control system. The calibrated model enables [14]:

- prediction of the dynamic evolution of grain moisture content and temperature;
- evaluation and validation of conventional PID controllers as well as intelligent control algorithms under different operating conditions;
- adaptive tuning of controller parameters during system operation based on continuously updated process information.

After identification the model yields $\text{RMSE} = 0.0078$ for grain moisture content and $\text{MAPE} = 3.4\%$, both well below the acceptance thresholds ($\text{RMSE} < 0.01$ and $\text{MAPE} < 5\%$), thereby confirming quantitative agreement with the experimental trajectories and the adequacy of the model for controller design.

3. Implementation of the mathematical model

To validate the proposed mathematical model and prepare it for integration into the automatic control system, a digital implementation was developed in the Python programming environment. Python was selected due to its extensive ecosystem of scientific computing libraries, including NumPy and SciPy for numerical analysis and Matplotlib for data visualization.

The simulation is based on a dynamic mathematical model in which the average grain moisture content and the average grain temperature are represented by a system of ordinary differential equations (ODEs). To improve numerical accuracy and ensure stable transient simulation, the governing equations are solved using an explicit time discretization scheme. The model parameters are obtained from the identification procedure described in the previous section.

Figure 1 presents the simulation results obtained using the developed digital model. The predicted responses demonstrate the temporal evolution of grain moisture content and temperature throughout the drying process, illustrating the progressive reduction of moisture and the corresponding increase in grain temperature. The simulation also provides quantitative information on the drying rate and the transient thermal behaviour until the process approaches steady-state conditions.

The developed digital model enables the prediction of process dynamics under different operating scenarios by varying the principal control parameters, including drying air temperature, airflow velocity, and the initial grain moisture content. Consequently, the model provides an effective platform for controller development, performance evaluation, process optimization, and implementation of intelligent control strategies within the proposed automatic control system.

The proposed system incorporates an adaptive hybrid PID controller, in which the controller parameters are adjusted according to the control error and the rate of change of grain moisture content. The controller was implemented in the Python simulation environment and evaluated under different operating conditions, including variations in initial grain moisture and external disturbances.

Quantitative comparison of the closed-loop responses shows that the adaptive hybrid PID controller reaches the target moisture content 22% faster than a conventional fixed-parameter PID controller under the same initial conditions and disturbances. Because the thermal power of the heaters remains essentially constant, this reduction in drying time corresponds to an equivalent 22% decrease in cumulative energy consumption.

It should be noted that all moisture content values presented in the figures are expressed on a dry basis. Therefore, the initial moisture content may exceed 100%, which is physically consistent with the properties of freshly harvested grain.

For automatic control systems, it is essential to evaluate how variations in process parameters affect the final drying quality and overall system performance. The principal performance indicators include the drying time required to achieve the target moisture content, the uniformity of moisture distribution throughout the grain layer, the stability of the grain temperature without overheating, and the overall energy efficiency of the drying process [1].

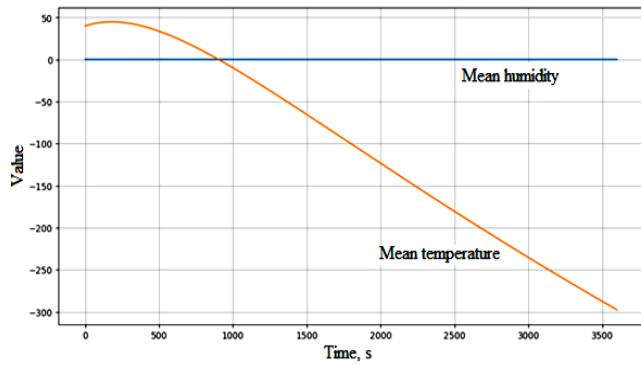


Fig. 1. Visualization of the digital simulation model of the grain drying process (moisture content X on dry basis, kg water/kg dry matter)

Increasing the drying air temperature accelerates moisture removal and reduces the overall drying time; however, excessive temperatures may lead to non-uniform moisture distribution, grain overheating, and deterioration of product quality. Therefore, selecting appropriate operating conditions requires balancing drying efficiency and product quality.

The numerical simulations performed in the Python environment, illustrated in Figure 2, provide a quantitative assessment of this trade-off by analysing the influence of the principal operating parameters on the dynamic behaviour of the drying process. The developed digital model enables the evaluation of alternative operating scenarios and supports the selection of optimal control strategies that simultaneously improve drying efficiency, maintain grain quality, and reduce energy consumption.

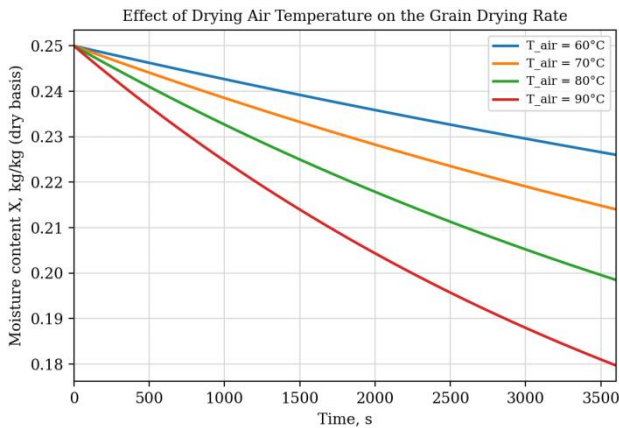


Fig. 2. Effect of drying air temperature on the grain drying rate (moisture content X on dry basis)

The simulation results demonstrate that increasing the drying air temperature T_{air} accelerates moisture removal and shortens the overall drying time. However, exceeding the optimum operating temperature may result in grain overheating, non-uniform moisture distribution, and deterioration of grain quality.

The mass transfer coefficient k_m is influenced by the grain layer thickness and the airflow intensity. An increase in k_m enhances the rate of moisture transport, thereby reducing the drying time. Nevertheless, excessively high values of k_m may lead to non-uniform drying due to intensified moisture gradients within the grain layer.

The influence of the mass transfer coefficient on the drying kinetics is illustrated in Figure 3. The simulation results indicate that a moderate increase in k_m improves the drying performance by reducing the processing time, whereas values exceeding the optimal operating range may cause instability in the moisture distribution and compromise drying uniformity.

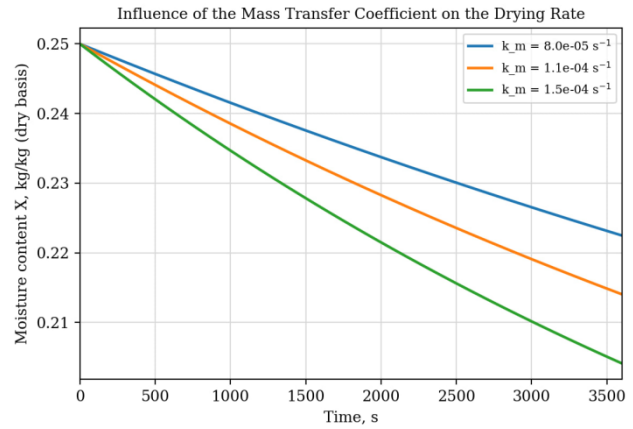


Fig. 3. Influence of the mass transfer coefficient on the drying rate (moisture content X on dry basis)

The initial grain moisture content is one of the primary factors determining the time required to achieve the target final moisture content X_{final} . Higher initial moisture levels significantly prolong the drying process due to the increased amount of moisture that must be removed. Conversely, grain with lower initial moisture content reaches the desired moisture level more rapidly, resulting in shorter drying times and reduced energy consumption.

The adequacy of the developed grain drying model determines its suitability for application in automatic control systems and controller design. The model is considered adequate if its predicted grain moisture content and temperature accurately reproduce the experimentally observed process dynamics. Model validation was performed using both qualitative and quantitative evaluation methods.

The graphical validation method involves comparing the experimentally measured and simulated moisture content and temperature profiles. The adequacy of the model is assessed by visually examining the agreement between the experimental and simulated curves, with particular attention to deviations in both magnitude and temporal response.

To provide an objective assessment of model accuracy, the Root Mean Square Error (RMSE) was employed as the primary performance metric:

$$RMSE_X = \sqrt{\frac{1}{N} \sum_{i=1}^N (X_{sim}(t_i) - X_{exp}(t_i))^2} \quad (11)$$

$$RMSE_T = \sqrt{\frac{1}{N} \sum_{i=1}^N (T_{sim}(t_i) - T_{exp}(t_i))^2} \quad (12)$$

Mean Absolute Percentage Error (MAPE):

$$MAPE_X = \frac{100\%}{N} \sum_{i=1}^N \frac{|X_{sim}(t_i) - X_{exp}(t_i)|}{X_{exp}(t_i)} \quad (13)$$

The RMSE and MAPE metrics provide a quantitative assessment of the predictive accuracy of the proposed mathematical model. In general, the model can be considered sufficiently accurate for implementation in an automatic control system when the prediction errors remain within acceptable limits (e.g., RMSE < 0.01 for grain moisture content and MAPE < 5%). These criteria indicate a high level of agreement between the simulated and experimental results.

If the calculated errors exceed the acceptable thresholds, the model should be refined by recalibrating its parameters, incorporating additional nonlinear effects, or accounting for external factors that may influence the drying process, such as ambient air humidity, non-uniform grain distribution, and variations in airflow velocity.

The validation results confirm that the proposed digital model accurately reproduces the dynamic behaviour of the grain drying process and is therefore suitable for engineering applications. The validated model provides a reliable basis for numerical simulations, controller design and evaluation, and investigation of the influence of operating conditions and external disturbances on the drying process. Furthermore, it constitutes the computational core of the proposed intelligent automatic control system and supports the development of advanced adaptive and predictive control strategies.

4. Conclusions

This study addresses an important scientific and engineering problem related to improving the efficiency of automatic control of the grain drying process through the development of an intelligent automatic control system based on mathematical modelling and modern digital technologies.

The conducted research investigated the grain drying process as a complex nonlinear control object and identified the key factors influencing drying quality and energy efficiency. A functional and structural architecture of the proposed automatic control system was developed, integrating sensing devices, actuators, software modules, and an information management environment into a unified intelligent control framework.

A mathematical model of the grain drying process was developed and implemented in the Python environment. The proposed model enables the analysis of the dynamic behaviour of the principal process variables, investigation of system operating modes, and evaluation of control algorithms without the need for costly experimental testing on industrial equipment.

The scientific novelty of the proposed approach lies in the combination of a process-oriented mathematical model of grain drying with an adaptive hybrid PID control strategy and an IoT-based feedback architecture. Unlike conventional fixed-parameter control approaches, the proposed controller uses the control error and the rate of change of grain moisture content to adjust its parameters under varying process conditions. The mathematical model provides a computational basis for evaluating the controller under changes in initial grain moisture and external disturbances, while the IoT architecture enables continuous acquisition of process data for feedback control. Thus, the original contribution is not the use of IoT or PID control individually, but their integration with an adaptive model-based control mechanism specifically formulated for the nonlinear and time-varying grain drying process.

The practical significance of the proposed approach is demonstrated by its applicability to both the modernization of existing grain drying facilities and the development of next-generation intelligent drying systems. The implementation of the proposed architecture can improve process stability, enhance grain quality, reduce energy consumption by approximately 22% relative to conventional fixed-parameter control, and provide continuous real-time monitoring and supervisory control of technological parameters.

The proposed system can be integrated with modern digital management platforms for agricultural enterprises, industrial SCADA systems, and cloud-based data acquisition and analytics services, thereby supporting remote monitoring, data-driven decision-making, and predictive process management.

It should be noted that the quantitative improvements reported above (including the 22% reduction in energy demand) were obtained from closed-loop simulations. Future research will therefore focus on the development of more advanced adaptive and predictive control strategies based on artificial intelligence and machine learning techniques, the implementation of a digital twin of the grain drying process for real-time optimization and diagnostics, and the experimental validation of the proposed intelligent control system under industrial operating conditions with comprehensive assessment of its technological, energy, and economic performance.

Disclosures

The authors declare no conflicts of interest.

Ethics approval and consent to participate

Not applicable. The study involved the design, mathematical modelling, simulation, and experimental evaluation of a grain drying automatic control system and did not involve human participants or animals.

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