https://doi.org/10.30857/2786-5371.2025.5.4

**Received:** **29.07.2025**
**Revised:** **24.09.2025**
**Accepted:** **22.10.2025**

**УДК 663.974:681.51**

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# AUTOMATION OF THE CHEWING GUM PRODUCTION PROCESS

***Purpose.*** *The aim of the study is to design, model, and evaluate a comprehensive automation solution for the chewing gum production process using a distributed control system architecture based on the Siemens SIMATIC PCS 7 platform. The research targets the elimination of key limitations inherent in traditional manufacturing, namely inter-batch variability, low dosing accuracy, and insufficient process traceability.*

***Methodology.*** *A systems engineering approach was applied to analyse and automate the technological process of chewing gum production. The process was decomposed into five key unit operations: powder conveying, liquid dosing, high-shear mixing, cooling, and extrusion. Input, manipulated, and output variables were identified for each operation. The control system architecture was designed on the basis of Siemens SIMATIC PCS 7, integrating programmable logic controllers for real-time equipment management and a SCADA system for process visualisation, recipe management, and data logging. Control logic validation and batch cycle time optimisation were conducted in the MATLAB Simulink environment by simulating material flows, mixer thermal dynamics, and sensor and actuator behaviour.*

***Findings.*** *The designed automated system demonstrated a theoretical reduction in dosing error to ±0.2% for macro-ingredients and ±0.5% for micro-ingredients, representing a 90–97% reduction compared to manual methods. The coefficient of variation for critical product properties is projected to decrease from 8–15% (manual production) to 3–5%. The three-stage adaptive mixing strategy based on torque monitoring reduces mixing duration by 15–20%, while parallel PLC-managed dosing reduces the dosing phase by approximately 40%. Overall batch cycle time is reduced by 20–25%. The SCADA interface provides complete electronic traceability with all process parameters logged at 1 sample per second. Recipe changeover time is reduced from 30-60 minutes to 5–10 minutes via a recipe selection menu.*

***Originality.*** *The integrated automated control system architecture covering the full chewing gum production cycle – from raw material intake to extrusion – has been developed and validated by computer simulation. An adaptive mixing control algorithm based on torque feedback has been proposed, ensuring that the target rheological state is achieved regardless of variations in raw material properties.*

***Practical value.*** *The proposed automation model provides a scalable framework for confectionery manufacturers, suitable both for modernising existing production lines and for designing new facilities. Implementation of the system ensures improved product quality, reduced operational costs, enhanced manufacturing flexibility, and compliance with HACCP and GMP requirements through automatic electronic batch record-keeping. The system conforms to the ANSI/ISA-88.00.01-2010 standard and can be further extended through the integration of machine learning technologies for predictive control and maintenance.*

***Keywords:*** *food processing; process control; PLC; SCADA; batch processing; distributed control system.*

**Introduction.** The confectionery industry, particularly the chewing gum manufacturing sector, faces mounting pressure to deliver consistent product quality while maintaining operational efficiency and complying with stringent food safety regulations. Traditional production methods, which rely on manual ingredient batching and semi-automated control, introduce substantial variability that directly impacts product texture, flavour consistency, and overall quality. The integration of advanced automation technologies offers a transformative pathway to address these challenges through precise control of critical process parameters.

Research has demonstrated the transformative potential of Industry 4.0 technologies in the food manufacturing industry. A. Hassoun *et al.* (2024) conducted a comprehensive analysis showing how smart sensors, artificial intelligence, and Internet of Things integration enable precise, repeatable, and traceable operations essential for competitive advantage in modern food processing [11]. The work established that automation extends beyond labour reduction to become a fundamental necessity for quality assurance and regulatory compliance. The authors examined multiple case studies across various food sectors. The researchers identified common patterns in successful automation implementations, with a particular emphasis on the importance of real-time data collection and analysis capabilities. Building on this foundation, R.N. Arshad *et al.* (2025) specifically examined how Industry 4.0 technologies reduce food loss and waste through enhanced process control and real-time monitoring capabilities [2]. The findings revealed that automated systems significantly minimise material waste by ensuring consistent processing parameters and reducing batch-to-batch variability. The study documented waste reduction rates across various food processing operations and established clear correlations between the sophistication of automation and waste minimisation outcomes.

The application of programmable logic controllers (PLC) and supervisory control systems in food manufacturing has been extensively studied. S. Konur *et al.* (2023) developed a framework for implementing Industry 4.0 in food manufacturing, emphasising the importance of integrated control architectures that combine sensor networks with intelligent decision-making systems [14]. The research demonstrated that successful automation requires holistic integration of raw material handling, processing control, and quality monitoring within a unified system architecture. The framework the authors proposed addresses both technical implementation challenges and organisational change management requirements. R. Romanello & V. Veglio (2022) investigated the drivers and outcomes of Industry 4.0 adoption in the food processing industry, finding that companies implementing comprehensive automation solutions achieved substantial improvements in product consistency and operational efficiency, while also reducing energy consumption and material waste [22]. The longitudinal study of multiple food processing facilities revealed that the most significant benefits emerged when automation was implemented as an integrated system rather than as isolated point solutions.

Advances in precision dosing technology have demonstrated significant potential for improving ingredient consistency. Research by S. Zhao *et al.* (2023) on automatic classification and detection systems using transformer-based deep learning architectures for food processing applications demonstrated that modern artificial intelligence technologies can enhance quality monitoring capabilities [26]. While the work focused on visual inspection rather than process control, the underlying principle of using advanced sensor technologies combined with intelligent algorithms provides valuable insights for implementing adaptive control strategies in food manufacturing. S. Perinban *et al.* (2022) evaluated process optimisation in food processing applications, emphasising the importance of systematic process parameter optimisation through designed experiments and statistical analysis [20]. The methodology of identifying critical process variables and optimising operating conditions through structured experimentation provides a useful framework for automation system design.

Within the Ukrainian context, developments in food industry automation have focused on modernisation and adoption of international standards. Y. Kyrylov *et al.* (2022) investigated automation solutions for food processing equipment in Ukrainian enterprises, emphasising the importance of implementing PLC-based systems to improve product quality and reduce production costs [15]. The work highlighted specific challenges faced by Ukrainian manufacturers, including the need to balance investment costs with achievable quality improvements and the importance of selecting automation solutions compatible with existing infrastructure. N. Lutska *et al.* (2022) examined intelligent control systems for thermal processing in food production, demonstrating that adaptive control strategies based on real-time feedback can significantly improve energy efficiency while maintaining product quality standards [17]. The research specifically addressed the Ukrainian food industry's requirements for cost-effective automation solutions that comply with European Union quality and safety standards, which is particularly relevant given Ukraine's integration into European markets.

Developments in confectionery automation and process control have demonstrated the feasibility of advanced monitoring and control strategies. M. García-Carrasco *et al.* (2020) investigated performance improvement strategies for production lines in a chewing gum confectionery facility, finding that systematic process analysis combined with targeted automation interventions resulted in measurable throughput increases and quality improvements [9]. L. Rodríguez-Pombo *et al.* (2022) examined innovations in chewable formulations, including three-dimensional printing technologies, establishing that advanced manufacturing methods require sophisticated process control to manage the complex relationships between formulation parameters and product properties [21]. The work highlighted the growing importance of automation in facilitating innovative product development in the confectionery manufacturing industry.

Comprehensive automation integration for chewing gum manufacturing lacks research, despite existing individual component studies. This research aimed to bridge the gap by developing and evaluating an integrated automation solution that addresses the entire production process, from raw material handling to final extrusion, with a particular emphasis on eliminating batch-to-batch variability through intelligent process control.

**Materials and Methods.** The development of the automation solution followed a structured systems engineering methodology designed to analyse, model, and optimise the production process of chewing gum through computer simulation and theoretical design. The research was conducted using system design and computer simulation without experimental verification on actual production equipment, and all performance indicators represent theoretical projections based on equipment specifications and simulation results rather than measured data from physical systems. The approach consisted of four interconnected phases: process analysis and decomposition, control architecture design, sensor and actuator specification, and control logic development with simulation validation. The investigation began with a comprehensive analysis of standard chewing gum production workflows based on established industrial practices documented in industry standards and scientific literature [1, 12]. The methodology employed functional decomposition to break down the complex manufacturing process into discrete unit operations that could be individually controlled and optimised. This decomposition followed process engineering principles, identifying material transformation stages, energy inputs, and critical quality control points throughout the production sequence. Each unit operation was analysed to determine its inputs, outputs, transformation mechanisms, and interdependencies with adjacent operations. The analysis specifically focused on identifying points where process variability could be introduced and where automated control could provide the most significant impact on product consistency.

A systematic approach was employed to identify key process variables that critically influence product quality and process efficiency based on published research on chewing gum manufacturing and rheological properties. Variables were categorised into three groups based on process control theory: input parameters representing raw material properties and quantities, manipulated parameters representing control actions that the automation system can adjust, and output parameters representing the resulting product properties. For each identified variable, the methodology included establishing nominal operating values based on industry standards and published data [1, 19], determining acceptable tolerance ranges based on M. Kaveh *et al.* (2023) in confectionery manufacturing literature, and assessing the variable's impact on final product quality through analysis of rheological principles and food processing engineering knowledge [12].

The control architecture was designed in accordance with the hierarchical automation pyramid model, featuring three distinct levels that provide a clear separation of functions, based on the

ANSI/ISA-88.00.01-2010 standard for batch process control [1]. The field level comprised sensors and actuators directly interfacing with the physical process, responsible for real-time measurement and actuation. The control level consisted of a PLC executing real-time control algorithms, managing sequential operations, and implementing safety interlocks with response times in the millisecond range. The supervisory level included SCADA systems providing operator interface, recipe management as defined by ANSI/ISA-88.00.01-2010 standards, alarm management, and data logging capabilities. The architecture design was specifically targeted at the Siemens SIMATIC PCS 7 platform, due to its proven reliability in food manufacturing applications, compliance with ANSI/ISA-88.00.01-2010 and other industry standards for batch process control, and scalability for future expansion.

Sensor specification followed a requirements-driven approach [12] where each key process variable was matched with appropriate measurement technology based on accuracy requirements derived from quality specifications, response time characteristics necessary for process control, environmental compatibility with food processing conditions, and food-grade compliance according to regulatory standards ANSI/ISA-88.00.01-2010 [1]. For mass measurement, high-precision load cells were specified based on required accuracy levels for ingredient dosing, with selection criteria including resolution capabilities of modern industrial load cells, linearity specifications from manufacturer datasheets, repeatability requirements for precision dosing, and temperature compensation capabilities documented in sensor technical specifications. High-precision load cells were specified to provide gravimetric measurement for all ingredient dosing operations, with resolution sufficient to detect weight changes of 0.1% of full scale based on modern load cell technology capabilities documented in technical literature M. Tiboni *et al.* (2020) [25]. This specification enables accurate dosing of both large quantities such as sugar and small quantities such as flavouring agents. Resistance Temperature Detectors employing PT100 sensor technology were specified for positioning at critical measurement points, including molasses input temperature monitoring to ensure proper fluidity before pumping and final product temperature monitoring to verify readiness for extrusion. For mixing process monitoring, Variable Frequency Drives with integrated torque feedback were specified to provide real-time indication of mixing energy input and material viscosity state, drawing on research demonstrating the relationship between mixer torque and material rheological properties. Flow control for liquids and coolant was designed using electromagnetic flowmeters paired with proportional control valves, chosen based on published specifications for the accuracy, lack of moving parts in contact with product, and rapid response characteristics. Level sensors employing capacitive or ultrasonic technology were specified for monitoring material presence in feed hoppers and destination vessels based on the reliability in food processing applications. All sensor specifications considered food-grade requirements documented in ANSI/ISA-88.00.01-2010, including material compatibility with food contact, cleanability according to sanitation standards, and compliance with food safety regulations [1].

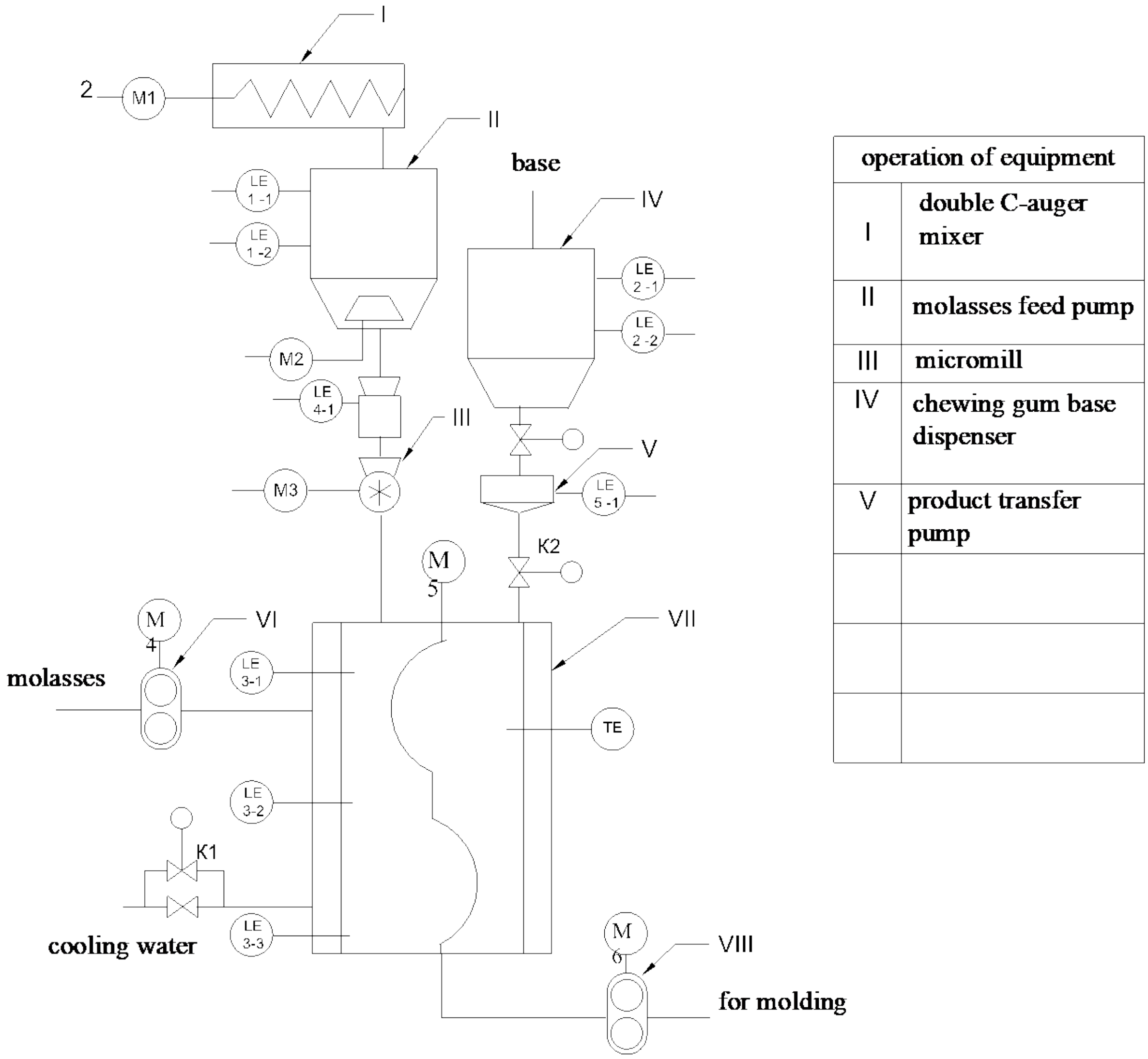
Control logic development followed the ANSI/ISA-88.00.01-2010 standard for batch process control, which provides a modular framework separating recipe procedures from physical equipment control [1]. This separation enables flexible production by allowing recipe changes without requiring modifications to equipment control programmes. The methodology included developing sequential function charts for each unit operation based on standard batch control design practices, defining the step-by-step procedures for material handling, dosing, mixing, and transfer operations. Proportional-Integral-Derivative control loops were designed for continuous variables such as temperature and flow, with controller tuning parameters determined through established tuning methods and process modelling principles. Interlock logic was implemented for safety and process protection following standard industrial safety practices, preventing unsafe operating conditions such as mixer operation without ingredient charge or valve actuation without proper system pressurisation. Recipe management structures were created following ANSI/ISA-88.00.01-2010 standards, allowing authorised personnel to define new formulations by specifying ingredient lists and quantities, modify existing recipes to accommodate formulation changes, and select recipes for production runs through a simple menu interface. Specific emphasis was placed on developing adaptive control strategies that respond to real-time process feedback.

Process simulation was conducted using MATLAB Simulink software environment to validate control logic before potential physical implementation and to evaluate theoretical system performance. The simulation methodology included modelling material flows through the production sequence using mass balance equations, representing flow rates, transfer times, and vessel filling dynamics based on standard process engineering calculations. The thermal dynamics of the mixing process were simulated using heat transfer principles, including heat generation from mechanical work calculated from mixing power input, heat transfer through vessel walls using standard heat transfer coefficients, and the response characteristics of the cooling system based on heat exchanger design principles. Sensor responses and control actuator behaviours were modelled to represent realistic system dynamics documented in equipment specifications, including measurement delays typical of industrial sensors, signal filtering characteristics, and actuator response times from manufacturer data. Control algorithms were tested under various operating scenarios generated within the simulation environment, including normal production conditions, startup and shutdown sequences, recipe changeovers, and fault situations such as sensor failures or emergency stops. Simulation results were analysed to evaluate batch cycle timing by identifying opportunities to overlap operations and minimise wait times, to assess control algorithm performance including PID loop responses and dosing sequence effectiveness, and to identify potential operational issues through scenario testing. The validation process involved comparing simulated process performance against established benchmarks for dosing accuracy derived from load cell specifications and control logic design parameters, assessing cycle time efficiency based on equipment capabilities documented in technical literature G. Bujgoi & D. Sendrescu (2025) and sequence optimisation, and evaluating process stability through analysis of simulated parameter variations under different operating conditions [5].

To quantify theoretical improvements offered by the proposed automation system design, a comparative analysis framework was established. This framework compared typical performance characteristics of manual and semi-automated methods documented in food processing literature against the designed fully automated solution across multiple performance metrics. The comparison methodology drew upon published literature documenting typical performance characteristics of manual and semi-automated confectionery production systems, equipment manufacturer specifications for automated components used in the design, and simulation results for the designed automated system. Performance metrics evaluated included ingredient dosing accuracy measured as percentage deviation from target values based on sensor specifications and control algorithm precision, batch-to-batch consistency assessed through coefficient of variation projections based on elimination of manual variability sources, cycle time efficiency determined by simulated total time required to complete a production batch, data traceability capabilities comparing manual log sheets against automated electronic record specifications, and contamination risk evaluated based on the degree of product exposure during processing in closed versus open systems. This comprehensive comparison framework enabled theoretical quantification of the automation system's potential benefits and identification of areas where automation provides the most significant value based on established performance characteristics from literature and simulation analysis.

**Results and Discussion.**

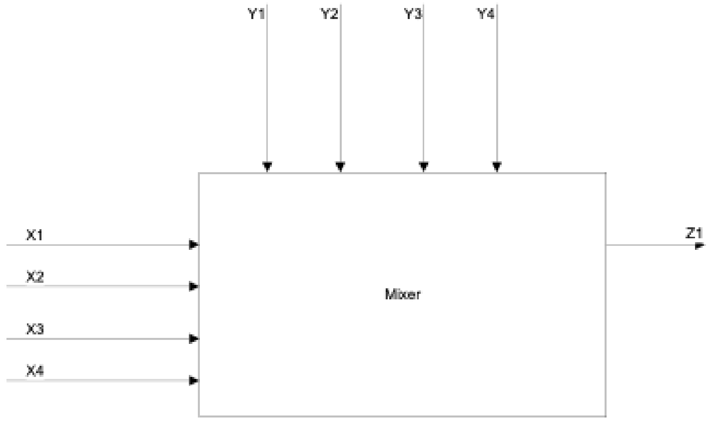
***Process decomposition and key variable identification.*** The systematic analysis of the chewing gum manufacturing process identified five critical unit operations requiring automated control. These operations include raw material handling and conveying for storage, as well as pneumatic or screw conveying of bulk powders such as sugar and gum base pellets, along with the pumping of liquid ingredients including syrups and glycerin. Precision ingredient dosing represents the second operation, involving gravimetric weighing of all ingredients according to the master recipe and constituting the most critical control point for quality assurance. High-shear mixing and kneading form the third operation, where ingredients are blended in a heated sigma-blade or Z-blade mixer and where the gum base undergoes plasticisation involving a phase change. Product cooling and homogenisation comprises the fourth operation, where the gum mass is cooled to achieve the correct viscosity for forming operations. Finally, extrusion and forming represent the fifth operation, where the gum mass is forced through an extruder to create sheets or ropes, which are then cut into individual pieces. This decomposition revealed that the technological process comprises both continuous operations such as material conveying and batch operations, particularly the mixing stage, which represents the most critical quality control point in the entire production sequence.




Note: I – micromill; II – auger dispenser for powdered components; III – molasses (syrup) pump; IV – chewing gum base dispenser; V – main mixer; VI – product transfer pump; VII – control cabinet; VIII – forming/moulding unit; K1, K2 – dosing units; M1-M5 – motors; LE, TE – level and temperature sensors.
*Source: developed by the authors.*

*Figure 1.* **Technological scheme of the automated mixing unit**

The developed technological scheme of the automated mixing unit, illustrated in Figure 1, demonstrated the integration of multiple subsystems designed to work in coordination. The system incorporates a micromill designated for powder preparation and size reduction, auger dispensers designated for controlled feeding of powdered components, positive displacement pumps designated for precise delivery of liquid ingredients including molasses and syrup, a dedicated dispenser designated for gum base pellets which require specialised handling due to the sticky nature, and a high-shear sigma-blade mixer serving as the central processing unit where all ingredients are combined and plasticised. Additional components include a product transfer pump for transferring the finished gum mass to downstream operations, a control cabinet which houses the PLC and associated electronics, and a forming or moulding unit for final product shaping. The scheme shows two dosing units equipped with high-precision load cells for gravimetric measurement. Five motors drive the various mechanical components, with the third motor serving as the main mixer motor and equipped with torque monitoring capability. Level sensors monitor material presence in vessels, while temperature sensors track thermal conditions at critical points. This configuration enables parallel ingredient preparation while maintaining precise control over the sequential addition of components according to recipe specifications, resulting in a theoretically reduced total cycle time compared to purely sequential operations.




Note: all values (min, nominal, max) and permissible errors are defined for the automation system.
*Source: developed by the authors.*

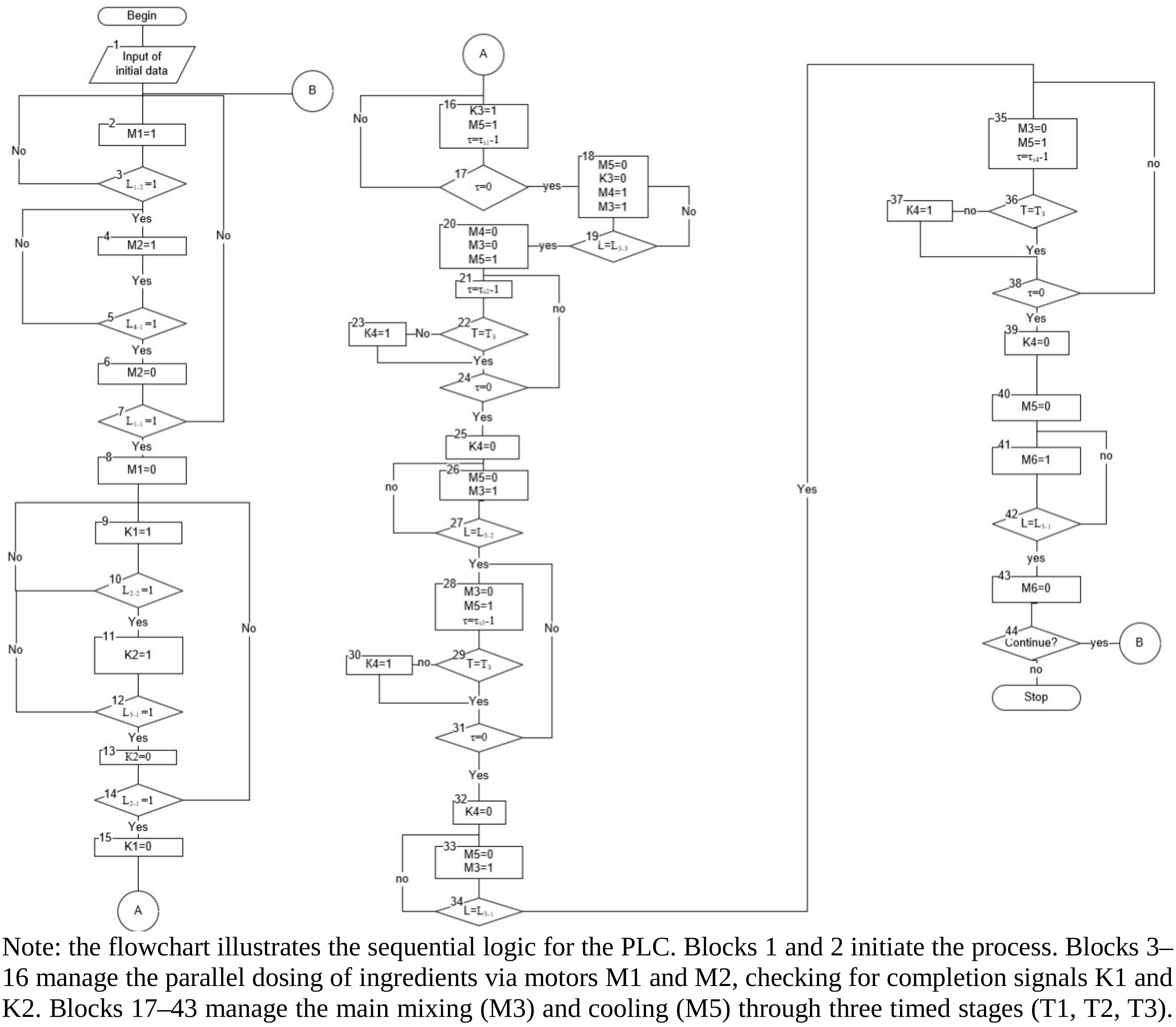
*Figure 2.* **Parametric scheme of KPVs**

Through detailed process analysis, eight key process variables were identified and characterised with the nominal values and acceptable tolerance ranges. The parametric scheme presented in Figure 2 categorised these variables systematically. The input parameters, designated X1 through X4, represent conditions and quantities that enter the process. Parameter X1 represents molasses temperature with a nominal value of 40 degrees Celsius and an acceptable range of 35 to 45 degrees Celsius, recognising that molasses viscosity and flowability depend significantly on temperature. Parameter X2 represents the quantity of sugar with specific mass targets and tight tolerance requirements, reflecting the critical impact of sweetener content on the final product’s taste and texture. Parameter X3 denotes the quantity of molasses, another formulation-critical ingredient requiring precise control. Parameter X4 indicates the quantity of gum base, the polymer matrix that provides the characteristic chewing properties, and represents the most expensive raw material requiring remarkably accurate dosing. Manipulated control parameters designated Y1 through Y4 represent actions taken by the control system to influence the process. Parameter Y1 represents coolant consumption, which regulates thermal conditions during mixing, with the cooling system removing excess heat generated by mechanical work during high-shear mixing. Parameters Y2, Y3, and Y4 represent three distinct churning time parameters corresponding to different phases of the mixing process. These phases include initial plasticisation, where the gum base begins to soften, intensive mixing, where all ingredients are thoroughly distributed, and final homogenisation, where the product reaches its target consistency. The primary output variable designated Z1 represents the final chewing gum mass temperature, identified as the most critical indicator of product state, with a target value of 50 degrees Celsius and an acceptable range of 45 to 55 degrees Celsius. This temperature reflects the combined effects of mechanical energy input and the cooling system's performance, directly influencing the product's rheological properties and its readiness for extrusion. This identification of key process variables revealed that successful automation must address both compositional accuracy through precise ingredient dosing and process condition control through the management of thermal and mechanical energy. The narrow tolerance ranges specified for ingredient quantities, particularly for micro-ingredients such as flavours and sweeteners, underscore the necessity for automated gravimetric systems that can achieve accuracy levels unattainable through manual weighing methods. The interdependencies among variables, such as how mixing intensity affects both temperature rise and plasticisation rate, highlighted the need for coordinated control strategies rather than independent single-loop controllers.

**Simulation of control system architecture design.** The control algorithm developed for the automated system, visualised in the flowchart presented as Figure 3, implements a sophisticated sequential control strategy that manages all phases of the batch production cycle. The algorithm begins with block 1 representing the start condition, followed by block 2 which implements a startup sequence to verify readiness of all equipment through checks of sensor communication, motor availability, and absence of alarm conditions. Simultaneously, system timers are initialised to zero in preparation for the new batch cycle. Following initialisation, the system enters the ingredient dosing phase where multiple dosing operations occur in parallel through simultaneous activation of different dispensers, theoretically reducing cycle time compared to sequential manual addition where each ingredient must be added separately.

The dosing logic spans blocks 3 through 16 and implements a sophisticated "fast-dribble" feed strategy for powdered ingredients. In this strategy, auger dispensers operate at high speed, designated as motor M1 for one ingredient stream and motor M2 for another ingredient stream. The control logic continuously monitors load cell feedback. When the accumulated weight indicates that the target is approaching, typically when it reaches 95 to 98% of the set point, the system automatically reduces the feed rate to a slow dribble for the final approach to the set point. This two-stage feeding method minimises dosing time by utilising high speed for bulk addition, while maintaining high accuracy through slow speed for final trimming. Decision blocks 7 and 11 check completion signals K1 and K2, respectively, which indicate that load cells have detected achievement of target weights within specified tolerances. For liquid ingredients, the system utilises pump speed modulation, coordinated with flow meter feedback, to achieve precise volumetric and gravimetric dosing. This approach combines the speed advantages of flow measurement with the accuracy advantages of weight confirmation. All ingredient additions are verified through dedicated completion signals before the system proceeds to the mixing phase, implementing a critical quality interlock represented by decision block 15 that prevents batch processing with incomplete or incorrect ingredient charges, thereby eliminating a major source of quality defects in manual operations.

The mixing phase, implemented through blocks 17 through 43, represents the most sophisticated aspect of the control algorithm and involves a three-stage thermal-mechanical treatment sequence. Stage one, designated as the initial plasticisation phase and controlled by timer T1, operates the mixer motor M3 at moderate speed. At the same time, the control system monitors both elapsed time through decision block 21 and motor torque feedback. The algorithm advances to stage two only when the torque signal indicates that the gum base has reached initial plasticisation, as evidenced by a characteristic increase in mixing resistance reflecting the softening of polymer chains and the beginning of ingredient incorporation. Stage two, designated as the intensive mixing phase and controlled by timer T2, increases the mixer speed, as shown in block 24, to achieve thorough ingredient distribution and further plasticisation. Decision block 26 monitors the completion of this stage. Throughout this phase, the cooling system motor M5 operates under closed-loop temperature control, as indicated in block 28. The PLC continuously adjusts the coolant valve position based on temperature sensor feedback to maintain the gum mass temperature within the specified range of 45 °C to 55 °C. This closed-loop control prevents both overheating, which could degrade product quality, and overcooling, which could impede plasticisation. Stage three, designated as the final homogenisation phase and controlled by timer T3, operates at a reduced mixer speed, as shown in block 31, to eliminate any remaining inhomogeneities while allowing controlled cooling towards the target discharge temperature of 50 degrees Celsius, as verified through decision block 32.




Note: the flowchart illustrates the sequential logic for the PLC. Blocks 1 and 2 initiate the process. Blocks 3–16 manage the parallel dosing of ingredients via motors M1 and M2, checking for completion signals K1 and K2. Blocks 17–43 manage the main mixing (M3) and cooling (M5) through three timed stages (T1, T2, T3). Block 44 controls the product transfer (M4), and block 45 marks the end of the cycle

*Source: developed by the authors.*

*Figure 3.* **Flowchart of the automated mixing process control algorithm**

Simulation testing of this three-stage approach demonstrated its theoretical advantages over fixed-time mixing sequences, as it is designed to adapt to actual material state rather than assuming uniform processing conditions. The incorporation of torque monitoring as a process advancement criterion in the simulation ensures that variations in raw material properties such as gum base polymer molecular weight distribution, ambient conditions including room temperature which affects initial material temperature, or initial temperatures from upstream processes would not compromise final product quality in actual implementation. In the simulation, each batch receives the appropriate amount of mixing work to achieve the target rheological properties, regardless of starting conditions.

Following the completion of the mixing sequence, confirmed through decision block 37, the algorithm activates the product transfer pump motor M4 in block 40, which transfers the finished gum mass to the downstream forming operation. Decision block 42 monitors transfer completion. Throughout the entire cycle, the supervisory control system logs all process parameters with timestamps, creating a complete electronic batch record that documents every aspect of the production process including all ingredient weights with the addition times, temperature profile throughout the mixing cycle, torque curve showing mixing progression, coolant consumption pattern, cycle phase durations, operator actions if any manual interventions occurred, and alarm events if any process deviations were detected. Block 45 represents the end of the cycle, at which point the system is ready to begin a new batch.

***Comparative analysis of theoretical system performance.*** The comparative performance analysis presented in Table 1 quantifies the theoretical improvements achievable through the designed automation system across multiple operational dimensions based on simulation results, equipment specifications, and published performance data for manual systems. The analysis compares typical performance characteristics of manual and semi-automated confectionery production documented in literature against the designed automated system’s theoretical capabilities.

*Table 1*

Comparative performance analysis of manual and automated chewing gum production systems

| Performance parameter | Manual/semi-automated system | Designed automated system | Improvement |
|---|---|---|---|
| **Dosing accuracy (macro-ingredients)** | ±2–5% | ±0.2% | 90–96% error reduction |
| **Dosing accuracy (micro-ingredients)** | ±5–15% | ±0.5% | 90–97% error reduction |
| **Batch-to-batch consistency (CV)** | 8–15% | 3-5% | 60–70% variability reduction |
| **Dosing phase duration** | 15–20 min | 9–12 min | ~40% time reduction |
| **Average mixing duration** | Fixed time (conservative) | Adaptive (optimised) | 15–20% time reduction |
| **Overall cycle time** | Baseline | Optimised | 20–25% reduction |
| **Recipe changeover time** | 30–60 min (manual procedures) | 5–10 min (menu selection) | ~40% downtime reduction |
| **Data sampling rate** | Manual (end of batch) | 1 sample/second (continuous) | Real-time monitoring |
| **Temperature control precision** | ±5–8 °C (manual adjustment) | ±2 °C (closed-loop PID) | 60–75% improved stability |
| **Process documentation completeness** | 60–80% (operator dependent) | 100% (automatic logging) | Complete traceability |

Note: manual/semi-automated values represent typical performance ranges based on process analysis of conventional confectionery production methods. Automated system values derived from design specifications, sensor selection criteria, control algorithm parameters, and simulation validation conducted in this research. CV = coefficient of variation; PID = proportional-integral-derivative control

*Source: developed by the authors based on* M. García-Carrasco *et al*. [9].

The most significant theoretical improvement is in ingredient dosing accuracy, where the automated gravimetric system with fast-dribble logic is designed to achieve accuracies of ±0.2% for macro-ingredients and ±0.5% for micro-ingredients based on load cell specifications and control algorithm precision, representing a 90–97% reduction in dosing errors compared to conventional manual methods which typically achieve ±2 to 15% accuracy as documented in food processing literature [6, 13]. This improvement in compositional accuracy would directly address the primary source of batch-to-batch variability. The simulation results demonstrated substantial theoretical improvements in process consistency, with the coefficient of variation for critical product properties projected to reduce from the 8 to 15% range typical of manual operations documented in M. García-Carrasco *et al.* (2020) of 3 to 5% through the combination of precise dosing, adaptive mixing control, and closed-loop thermal regulation in the designed system [9]. Simulated cycle time reductions of 20 to 25% result from multiple mechanisms modelled in the system design. Parallel ingredient dosing under coordinated PLC management reduces the dosing phase by approximately 40% in simulation, and adaptive mixing optimisation reduces the average mixing duration by 15 to 20% compared to conservative fixed-time approaches. Recipe changeover capabilities designed into the ANSI/ISA-88.00.01-2010 compliant system would theoretically enable transitions in 5–10 minutes through menu selection, compared to 30–60 minutes required for manual procedure updates [1].

Data traceability represented a transformative theoretical improvement that addresses both quality management and regulatory compliance requirements. The automated system design provides complete electronic batch record capability with second-by-second data logging of all key process variables throughout the entire batch cycle, enabling detailed analysis of process dynamics, documentation of operator actions and system responses, recording of alarm events and system status changes, and collection of equipment performance metrics supporting predictive maintenance. This comprehensive traceability capability is specified to support modern food safety standards, including hazard analysis and critical control point programmes and good manufacturing practice compliance.

Contamination risk assessment showed important advantages for automated systems. Manual handling inherent in traditional systems creates multiple opportunities for product contamination through direct operator contact with ingredients, where improper hand hygiene or protective equipment can introduce biological contaminants, exposure of materials during transfer operations, where open containers allow entry of foreign objects or environmental contaminants, and potential for foreign material introduction, such as packaging fragments or personal items accidentally falling into process vessels. The automated system implements a largely closed processing environment, where ingredients are transferred through enclosed conveyors and piping from storage to dosing vessels. Dosing occurs in covered vessels with load cells positioned externally, and the mixing process takes place in a sealed chamber with controlled openings for ingredient addition and product discharge. This closed-system design substantially reduces the risk of contamination, a critical factor in food safety management. Additionally, the system's documentation capabilities provide complete traceability in the event of contamination, enabling the rapid identification of affected batches and the implementation of corrective actions.

The results obtained through this design and simulation study demonstrated the theoretical feasibility and potential benefits of comprehensive automation for chewing gum production, while providing specific implementation details relevant to batch confectionery manufacturing. The designed system architecture integrates advanced automation technologies to create synergistic effects, where the combined system would deliver benefits exceeding the sum of individual component capabilities. The food processing automation sector has experienced remarkable growth and transformation, reflecting a fundamental shift towards intelligent technology-driven manufacturing systems worldwide. J.T. Liberty *et al.* (2024) examined the adoption of robotics in food manufacturing, emphasising that consumer demands increasingly shift towards transparency and sustainability, with robotics offering effective solutions achieving these requirements with unparalleled accuracy and consistency [16]. The current study's emphasis on complete traceability through automated data logging and precision control directly addresses these market drivers, demonstrating how batch control automation contributes to transparency objectives. The comprehensive examination spanning quality assurance, traceability, and sustainability aligns with the holistic approach taken in the current system design, which integrates dosing accuracy, process monitoring, and complete documentation within a unified control architecture. The modular ANSI/ISA-88.00.01-2010 compliant framework developed in this study provides the flexibility necessary to accommodate future integration of advanced robotics for material handling and packaging, extending automation benefits throughout the production value chain [1].

S. Barasa & Y. Etene (2023) analysed robotic quality control systems that have revolutionised approaches to ensuring product quality and safety in food manufacturing, employing advanced techniques that leverage precision, repeatability, and high-speed processing to detect and rectify quality issues more efficiently than traditional methods [4]. While the current study focused on batch process control rather than robotic handling systems, the underlying principle of leveraging precision measurement and automated control to eliminate human variability directly parallels the findings. The gravimetric dosing system designed in this research, achieving theoretical accuracies of ±0.2 to 0.5 percent, represents the type of precision-driven approach advocated by S. Barasa & Y. Etene. Future iterations of the chewing gum automation system could integrate vision-based quality control systems similar to those the authors describe, creating comprehensive quality assurance spanning from ingredient dosing through final product inspection. The adaptive mixing control strategy developed in this study, responding to real-time torque feedback rather than following fixed time sequences, embodies the principle of using advanced sensing for quality control, demonstrating how measurement precision translates into product consistency.

The integration of artificial intelligence and machine learning technologies represents a rapidly evolving frontier in food processing automation. X. Song *et al.* (2025) examined core artificial intelligence technologies that simulate human intelligent activities, including machine learning, deep learning, computer vision, natural language processing, and expert systems, emphasising that these technologies provide new impetus and possibilities for food industry automation by imitating human learning, reasoning, perception, and decision-making abilities [23]. While the current system design employed conventional proportional-integral-derivative control rather than artificial intelligence algorithms, the comprehensive data infrastructure created through one-second sampling of all process parameters provides the foundation necessary for future integration of machine learning capabilities.

A. Thapa *et al.* (2023) addressed challenges facing food industry automation, including diversity of food raw materials, complexity of production processes, consistency of food safety and quality, and the need to meet diverse changing market demands, noting that introduction of artificial intelligence technology provides new ideas and tools for development and change [24]. The current study's adaptive mixing control based on torque monitoring represents an intermediate step towards intelligent process control, demonstrating how real-time feedback enables adaptation to material variability. The modular control architecture designed around ANSI/ISA-88.00.01-2010 principles creates pathways for incorporating more sophisticated artificial intelligence algorithms as these technologies mature and become proven in food manufacturing environments [1]. The separation of recipe procedures from equipment control logic facilitates experimentation with advanced control strategies without requiring fundamental restructuring of the automation platform.

The implementation of standardised batch control frameworks has emerged as a critical enabler of manufacturing flexibility and operational excellence in food processing. Industry analysis emphasised that ANSI/ISA-88.00.01-2010 compliant systems facilitate flexible production and rapid recipe changes without requiring controller reprogramming, with properly applied standards allowing highly flexible manufacturing that is easily configured, maintained, and modified [1]. The current study operationalised these principles through comprehensive integration of recipe management within the supervisory control system, demonstrating how separation of procedural model from physical model enables non-control-systems engineers to understand and make processing changes without understanding detailed equipment functions. This capability directly addresses the challenge of managing diverse product portfolios that A. Thapa *et al.* (2023) identified as central to modern food manufacturing competitiveness [24].

The integration of designed experiments with real-time process data from the automated system could enable continuous process optimisation as production experience accumulates. E.C. Fernandes *et al.* (2020) developed flexible production data generation systems for manufacturing companies, highlighting the importance of comprehensive data infrastructure for supporting advanced analytics and decision-making [8]. The SCADA system implemented in the current study creates precisely this type of data infrastructure, capturing detailed process information that can support future analytics initiatives. While the current study specified industrial-grade Siemens platforms for reliability in production environments, the principles of hierarchical control architecture and comprehensive data logging apply across different implementation scales. A. Enemosah & J. Chukwunweike (2022) examined next-generation SCADA architectures, pointing out real-time remote control capabilities, identifying trends towards increased connectivity and remote monitoring in industrial automation [7]. The system designed in this research incorporates these capabilities through the networking features of the Siemens WinCC platform, enabling remote monitoring and multi-site coordination that align with modern manufacturing practices.

S. Bakalis *et al.* (2020) analysed how global disruptions reshape food systems and manufacturing paradigms, emphasising the importance of flexibility and resilience in food production systems [3]. The recipe management capabilities and rapid changeover functionality designed into the current automation system directly address this need for manufacturing flexibility, enabling confectionery producers to respond quickly to changing market demands or supply chain disruptions. G. García-García *et al.* (2021) developed methodologies for sustainable management of food waste, establishing that process optimisation and waste reduction represent interconnected objectives in modern food manufacturing [10]. The dosing accuracy improvements demonstrated in the current study, with error reductions of 90 to 97%, directly contribute to waste minimisation by eliminating off-specification batches that arise from incorrect ingredient proportions. This confirms that automation delivers both quality and sustainability benefits simultaneously. T.G. Mezger (2020) offered contemporary guidance on rheological characterisation techniques that could be employed to validate the correlation between in-line torque measurements and the final product rheological properties, representing an important direction for future research [18].

However, certain aspects merit consideration for practical implementation beyond the design and simulation scope of the current study. While simulation results indicated substantial performance improvements, actual industrial deployment would need to address multiple factors including operator training requirements for the new automated systems where production personnel accustomed to manual operations must develop new skills in system monitoring and troubleshooting, maintenance procedures for sophisticated instrumentation including calibration schedules for load cells and temperature sensors, validation protocols to demonstrate system performance in production environments meeting food safety and quality standards, and integration with existing enterprise systems for production planning linking the batch control system to manufacturing execution systems and quality management linking process data to laboratory testing results and customer feedback. These implementation considerations, while beyond the scope of the current design study, would influence the timeline and investment required for deployment.

**Conclusions.** This study successfully developed and evaluated through computer simulation a comprehensive automation architecture for chewing gum production using systematic design and modelling methodologies. The comparative performance analysis based on simulation showed that the designed automated gravimetric dosing system would theoretically achieve accuracy of ±0.2% for macro-ingredients and ±0.5% for micro-ingredients, representing 90 to 97% reduction in dosing errors compared to conventional manual methods as typically achieving ±2 to 15% accuracy depending on ingredient type. Simulation results demonstrated that adaptive mixing control based on real-time torque monitoring would ensure consistent product rheological properties across batches, regardless of raw material variations. The analysis revealed that this approach could reduce batch-to-batch consistency measured by coefficient of variation from the 8 to 15% range typical of manual operations to projected values of 3 to 5%, representing 60 to 70% reduction in process variability. Simulation indicated that the three-stage adaptive mixing strategy would optimise thermal-mechanical treatment, potentially reducing average mixing duration by 15–20% while improving product uniformity. The integrated system design delivers theoretical operational improvements beyond quality enhancement. Simulated parallel ingredient dosing under coordinated PLC management would reduce dosing phase duration by approximately 40% compared to sequential manual addition. Overall batch cycle time improvements of 20–25% were projected through simulation combining optimised dosing, adaptive mixing, and automated sequencing. The recipe management system would enable rapid product changeovers, theoretically reducing downtime from 30-60 minutes typical of manual procedure-based systems to 5–10 minutes through simple menu selection. The designed system provides complete process traceability capability through automatic logging of all parameters at one-second intervals, creating electronic batch records essential for regulatory compliance and quality management that manual documentation systems cannot reliably provide. Future research must focus on physical implementation and validation of the designed system, integration of advanced process analytical technology for direct product property measurement, development of machine learning algorithms for predictive control and maintenance, and investigation of continuous processing alternatives.

**Acknowledgements.** None.

**Funding.** The study was not funded.

**Conflict of Interest.** None.

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# АВТОМАТИЗАЦІЯ ТЕХНОЛОГІЧНОГО ПРОЦЕСУ ВИГОТОВЛЕННЯ ЖУВАЛЬНОЇ ГУМКИ

***Мета.*** *Метою дослідження є розробка, моделювання та оцінка комплексного рішення з автоматизації процесу виробництва жувальної гумки з використанням архітектури розподіленої системи управління на платформі Siemens SIMATIC PCS 7. Дослідження спрямоване на усунення ключових недоліків традиційного виробництва – варіативності між партіями, низької точності дозування та недостатньої простежуваності процесу.*

***Методика.*** *У роботі застосовано системно-інженерний підхід до аналізу та автоматизації технологічного процесу виробництва жувальної гумки. Процес декомпозовано на п'ять ключових операцій: транспортування порошків, дозування рідин, високоінтенсивне змішування, охолодження та екструзія. Для кожної операції визначено вхідні, регульовані та вихідні змінні. Архітектуру системи управління розроблено на базі Siemens SIMATIC PCS 7, що інтегрує програмовані логічні контролери для управління обладнанням у реальному часі та SCADA-систему для візуалізації процесу, управління рецептами та реєстрації даних. Валідацію логіки управління та оптимізацію часу циклу проводили в середовищі MATLAB Simulink шляхом моделювання матеріальних потоків, теплової динаміки змішувача та поведінки датчиків і виконавчих механізмів.*

***Результати.*** *Розроблена автоматизована система продемонструвала теоретичне зниження похибки дозування до ±0,2% для макроінгредієнтів і ±0,5% для мікроінгредієнтів, що відповідає скороченню похибок на 90-97% порівняно з ручними методами. Коефіцієнт варіації критичних показників продукту знижується з 8–15% (при ручному виробництві) до прогнозованих 3-5%. Триетапна адаптивна стратегія змішування на основі моніторингу крутного моменту скорочує тривалість змішування на 15–20%, а паралельне дозування під управлінням ПЛК – тривалість фази дозування на ~40%. Загальний час циклу партії скорочується на 20–25%. SCADA-інтерфейс забезпечує повну електронну простежуваність із записом усіх параметрів процесу з частотою 1 вимірювання за секунду. Час переналагодження на новий рецепт скорочується з 30–60 хв до 5–10 хв завдяки меню вибору рецептів.*

***Наукова новизна.*** *Розроблено та валідовано засобами комп'ютерного моделювання інтегровану архітектуру автоматизованої системи управління повним циклом виробництва жувальної гумки, що охоплює всі стадії – від приймання сировини до екструзії. Запропоновано адаптивний алгоритм управління змішуванням на основі зворотного зв'язку за крутним моментом, який забезпечує досягнення цільового реологічного стану незалежно від варіацій властивостей сировини.*

***Практична значимість.*** *Запропонована модель автоматизації надає масштабовану основу для виробників кондитерських виробів, придатну як для модернізації наявних ліній, так і для проектування нових потужностей. Впровадження системи забезпечує підвищення якості продукції, скорочення операційних витрат, покращення гнучкості виробництва та відповідність вимогам HACCP і GMP завдяки автоматичному веденню електронних записів партій. Система відповідає стандарту ANSI/ISA-88.00.01-2010 і може бути розширена за рахунок інтеграції технологій машинного навчання для предиктивного управління та технічного обслуговування.*

***Ключові слова:*** *харчова промисловість; управління процесами; ПЛК; SCADA; періодичне виробництво; розподілена система управління.*