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Selection and application of control principles in beer brewing processes based on MCDA framework

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Abstract

Beer production is a complex process involving multiple stages with diverse control requirements, including nonlinear biological reactions and energy-intensive operations. To ensure consistent product quality, operational efficiency, and compatibility with digital manufacturing technologies, the selection of appropriate control strategies is critical. This study presents a structured methodology for the evaluation and integration of control system principles tailored to beer production. The process was decomposed into key operational stages, mashing, boiling, fermentation, conditioning, and packaging, and specific control objectives were defined for each. A multi-criteria decision analysis (MCDA) framework, based on the Analytic Hierarchy Process (AHP), was applied to assess six control methods: PID, cascade, feedforward, fuzzy logic, model predictive control (MPC), and On/Off control. Evaluation criteria included control performance, ease of implementation, adaptability, energy efficiency, cost-effectiveness, and Industry 4.0 integration potential. The results indicated that a hybrid control approach, combining PID, fuzzy logic, and MPC, offers optimal performance across the production workflow. An integrated control architecture was designed to coordinate these methods within a scalable and intelligent automation framework. The proposed solution supports real-time monitoring, improved process stability, and readiness for future digital upgrades, providing a practical model for intelligent brewery operations.

Keywords

Beer Production; Control System Design; Fuzzy Logic Control; Industry 4.0; Model Predictive Control; Process Automation.

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Introduction

Beer production holds a vital place in the global food and beverage industry, not only for its historical and cultural significance but also for its substantial contribution to agricultural resource utilization, technological advancement, and economic development. The brewing sector supports a wide range of upstream and downstream industries, from barley and hops cultivation to distribution, packaging, and equipment manufacturing, making it a crucial driver of food processing innovation. The global beer market is projected to continue its expansion, fueled by changing consumer preferences, urbanization, and the proliferation of both large-scale breweries and craft microbreweries (Bamforth, 2016; Hornink, 2024).

With this growing demand comes an equally pressing need for high-quality, diverse, and consistent beer products. Modern consumers expect flavor stability, precise alcohol content, and microbial safety across different batches and brands. This expectation places considerable stress on production systems, especially given the biological nature of key processes such as fermentation and maturation (Bamforth & Fox, 2023). In addition, rising energy costs, water usage concerns, environmental regulations, and sustainability objectives have pushed breweries to reconsider traditional manufacturing approaches.

Despite centuries of development, beer production continues to face several critical operational challenges. These include high energy consumption during boiling and cooling phases, uncontrolled or suboptimal fermentation dynamics due to biological variability, process inconsistencies caused by raw material fluctuations, and hygiene risks in multi-stage handling systems. Moreover, legacy control systems, often manual or partially automated, struggle to detect and correct early deviations, resulting in product losses, increased waste, and inefficiencies. These challenges are further compounded by the complex interplay of thermal, chemical, and biological

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sub-processes within brewing, which require precise monitoring and timely control interventions (Abunde et al., 2019).

To address these growing complexities, breweries have increasingly begun adopting automated control systems, which play a pivotal role in regulating critical process parameters such as temperature, pressure, pH, dissolved oxygen, and flow rate. The use of digital control technologies not only improves operational accuracy but also supports energy efficiency, data-driven decision-making, and predictive maintenance. For instance, accurate temperature control during fermentation is vital to prevent the formation of unwanted by-products like diacetyl and fusel alcohols, which can compromise the flavor and aroma of the final product. Similarly, maintaining optimal pH levels during mashing ensures effective enzyme activity and extraction efficiency, influencing both yield and taste.

Several studies have demonstrated that automation significantly reduces specific energy consumption in breweries. For instance, Abunde et al. (Abunde et al., 2019) reported 8–15 % reductions in brewhouse thermal load and 10 % shorter cooling cycles after implementing automated heat-recovery and MPC-based energy scheduling. Similarly, Hermanucz et al. (Hermanucz & Geczi, 2022) documented up to 20 % energy savings in pilot breweries through advanced temperature sequencing and pump optimization.

Several research efforts have explored advanced control strategies for beer production. Chai et al. (Chai et al., 2022) demonstrated the effectiveness of fuzzy logic and predictive control in managing nonlinear fermentation temperature dynamics, highlighting its robustness in uncertain conditions. Abunde et al. (Abunde et al., 2019) proposed a model predictive control (MPC) framework for optimizing brewhouse energy consumption and reducing peak demand loads. Other studies have analyzed the implementation of SCADA systems for real-time monitoring (De Oliveira et al., 2021), neural network-based prediction models for fermentation kinetics, and the integration of IoT technologies in brewery environments (Tamo & Hilario-Tacuri, 2020). However, most of these investigations focus narrowly on isolated units or single-stage applications without considering the full complexity of the beer production lifecycle or the interdependencies between stages such as mashing, lautering, fermentation, and conditioning.

Currently, literature lacks a comprehensive, system-level approach that combines classical and intelligent control principles into a coherent architecture. In particular, there is a significant research gap in the selection and integration of suitable control strategies that are tailored to the multivariable, nonlinear, and dynamic characteristics of beer production while also enabling flexibility, adaptability, and connectivity within Industry 4.0 frameworks.

This research aims to bridge this gap by developing a structured methodology for the selection and integration of control system principles in beer production using a multi-criteria decision analysis (MCDA) approach (Kizielewicz et al., 2021; Shekhovtsov et al., 2021). This approach considers process dynamics, control complexity, implementation feasibility, and technological compatibility across all major production stages. Specifically, the study examines the combined use of PID control, fuzzy logic, cascade control, and MPC to ensure optimal process performance. The methodology also evaluates the interoperability of these control principles with modern SCADA platforms, edge computing systems, and IoT-based data acquisition.

The novelty of this work lies in the unified framework that not only selects the most appropriate control strategies for each brewing stage but also emphasizes process-wide integration and responsiveness. It further contributes to the field by aligning traditional control theory with smart manufacturing principles, thus providing a foundation for intelligent, adaptive, and energy-efficient brewery operations. The outcome is a scalable and implementable control system design that enhances both operational robustness and product quality, while supporting digital transformation goals in the brewing industry.

Materials and methods

The methodological approach adopted in this study aims to systematically evaluate, select, and integrate appropriate control strategies for various stages of the beer production process. Given the complexity, multivariable nature, and nonlinear dynamics of brewing operations, the methodology combines qualitative process analysis with quantitative decision-making tools. The study is structured around five key methodological phases, process analysis, definition of control requirements, identification of suitable control methods, application of MCDA, and the design of an integrated control architecture (Figure 1).

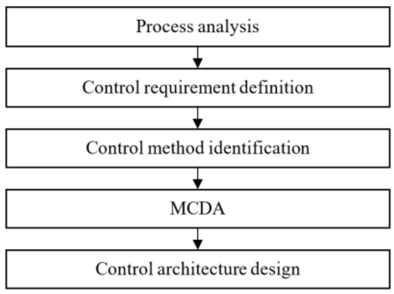

Figure 1. General research methodology (own elaboration)

Preparation of substituted cinnamic acids: The beer production process was first decomposed into its major operational stages, namely, mashing, lautering, boiling, fermentation, conditioning, and packaging (Figure 2). In the mashing stage, crushed malt is mixed with hot water to activate enzymes that convert starches into fermentable sugars.

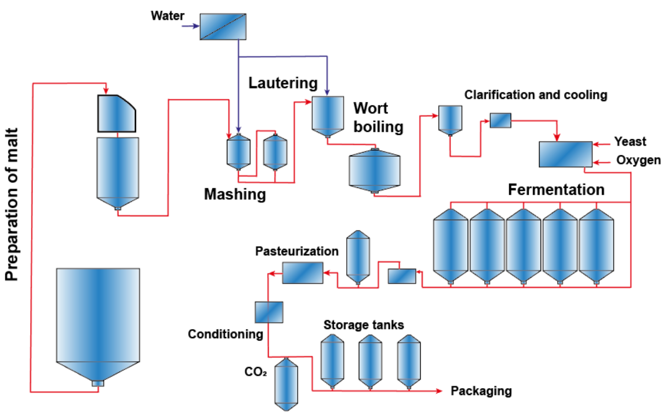

Figure 2. Process flow diagram of beer production process.

Lautering follows, where the liquid wort is separated from the spent grain. During boiling, the wort is sterilized and hops are added for bitterness and aroma. The fermentation stage involves yeast converting sugars into alcohol and CO_2. Conditioning allows the beer to mature and develop clarity and flavour. Finally, packaging ensures product stability and prepares the beer for distribution. For each stage, key process variables (temperature, pressure, pH, flow rate, dissolved oxygen) and process constraints were identified based on industrial brewing practices and literature (Coldea et al., 2014; Zamudio Lara et al., 2022) (Table 1).

Process stage	Key process variables	Typical Operating Range / Assumptions	Process Constraints
Mashing	Temperature, pH, time	Temp: 62–68 °C; pH: 5.2–5.6; Time: 60–90 min	Enzyme activity is sensitive to temperature/pH; excessive temperature inactivates enzymes
Lautering	Flow rate, turbidity, bed pressure	Flow: 1–2 L/min/m²; Pressure drop: <0.5 bar	Avoid channeling and grain bed compaction; maintain uniform filtration
Boiling	Temperature, evaporation rate, pressure	Temp: ~100 °C; Pressure: atmospheric or slightly above	Must reach full boil for sterilization; excessive evaporation leads to volume loss
Fermentation	Temperature, pH, dissolved oxygen, pressure	Temp: 18–22 °C (ales), 8–14 °C (lagers); pH: 4.0–4.5; DO: 8–10 ppm	Yeast activity depends on temp/DO; CO_2 buildup must be controlled
Conditioning	Temperature, pressure, dissolved CO_2	Temp: 0–4 °C; CO_2: 2.2–2.8 volumes	Low temp required for clarity; over-carbonation risks pressure buildup
Packaging	Flow rate, CO_2 pressure, temperature	Flow: variable; CO_2: 2.4–2.6 volumes; Temp: <10 °C	Maintain sterility; consistent fill volumes; prevent foaming and oxygen pickup

Table 1. Key process variables and process constraints.

While temperature, pressure, pH, flow rate, and dissolved oxygen are the dominant process variables, additional parameters, such as turbidity during lautering, specific gravity during fermentation, and CO_2 concentration during conditioning, can further enhance control precision. Future implementations should integrate inline refractometers and CO_2 sensors within the same control framework to improve stability and fault detection. Process dynamics were qualitatively assessed in terms of time-dependency, control sensitivity, disturbance levels, and actuator responsiveness. This step involved collaboration with brewery engineers and review of existing process data to construct simplified dynamic models (when available) or empirical rule-based relationships. These models supported the identification of critical control loops and potential automation gaps across the production line.

Control requirements definition: Following the decomposition of the beer production process into its fundamental operational stages, specific control objectives were formulated to address the key parameters that directly influence product quality, process stability, and operational efficiency. These objectives reflect the functional needs of each stage and provide a foundation for control system selection and performance evaluation.

In the mashing stage, temperature regulation is critical to ensure optimal enzymatic activity for starch-to-sugar conversion. The control system must maintain the mash temperature within a narrow band (typically 62–68 °C), despite potential disturbances such as variations in feed water temperature or inconsistent thermal conductivity of the mash. Similarly, during fermentation, precise temperature control is required to maintain yeast activity and avoid the formation of undesirable by-products. Given the sensitivity of yeast metabolism to thermal conditions, the system must ensure slow, stable temperature changes and be capable of responding to gradual heat generation by metabolic activity. pH control is essential during wort preparation to maintain the ideal enzymatic environment. The mashing process requires pH to be maintained in the range of 5.2 to 5.6 to optimize enzyme performance and prevent unwanted protein precipitation. This requires a control system capable of regulating the addition of acid or base in response to real-time pH fluctuations, which may be influenced by water composition, grain type, and thermal variations.

During the transfer and packaging stages, precise flow and pressure control are required to ensure uniform liquid handling, reduce turbulence, and avoid product losses. Sudden changes in flow rates or pressure levels can lead to foaming, oxygen pickup, and inconsistent fill levels. Therefore, control systems in these stages must be fast-acting and capable of minimizing overshoot, especially during start-stop transitions. Oxygen dosing control is critical during wort aeration, immediately after boiling and before fermentation. The dissolved oxygen level must be increased to around 8–10 ppm to promote healthy yeast growth. Over-aeration or under-aeration can both negatively impact fermentation kinetics and product quality. Consequently, the control mechanism must support fine-tuned regulation of oxygen flow and distribution.

In both fermentation and storage tanks, liquid level control is necessary to prevent overflow, ensure volume consistency, and maintain hydrostatic pressure conditions. These tanks often require level measurement and actuation systems that respond smoothly to slow fill or draw-down processes, which are typical in batch or semi-continuous operations.

Identification of candidate control strategies: To effectively address the control objectives defined for each stage of the beer production process, a range of candidate control strategies was identified, taking into consideration both traditional control approaches and more advanced, intelligent methods. The selection process was grounded in the dynamic characteristics of the process stages, the specific requirements of each control loop, and the broader goals of automation, efficiency, and integration within digital manufacturing systems. This study examines a range of control strategies, PID, cascade, feedforward, fuzzy logic, model predictive, and On/Off control, to determine which approach is most suitable for the process under analysis.

PID control operates by continuously correcting the deviation between a measured variable and its desired value through proportional, integral, and derivative actions (Borase et al., 2021). The proportional term provides immediate response, the integral term removes steady-state error, and the derivative term predicts future trends to improve stability

(Dubey et al., 2022). Effective tuning ensures fast response without overshoot. Modern implementations include anti-windup protection, derivative filtering, and adaptive gain adjustment to maintain performance under variable load conditions (Hägglund & Guzmán, 2024; Mohindru, 2024).

Cascade control extends the PID concept by introducing an inner and an outer loop. The inner loop rapidly stabilizes a secondary variable that directly influences the main controlled variable (Liu et al., 2024). This hierarchical structure increases disturbance rejection capability and minimizes the effect of intermediate process fluctuations. Proper coordination between inner and outer loop dynamics is essential for achieving overall stability (Chen et al., 2024). Feedforward control functions as a proactive mechanism. It measures known disturbances before they affect the process and applies compensatory action directly to the actuator. This minimizes transient deviations and complements feedback control, which reacts only after an error has occurred. The accuracy of feedforward performance depends on the reliability of the disturbance model and sensor calibration (Duan & Kang, 2024).

FLC represents a knowledge-based approach that does not require an explicit mathematical model of the system (Eshbobaev et al., 2024). The controller uses linguistic variables (for example, “error is small” or “change is fast”) and rule-based reasoning to determine control actions. The inference mechanism combines expert rules and computes an output through fuzzification, rule evaluation, and defuzzification steps. FLC allows smooth nonlinear control behavior, robust performance under uncertainty, and easy interpretability by human operators (Mohindru, 2024). MPC is an optimization-based technique that calculates control actions by predicting future process behavior over a defined time horizon (Hu et al., 2021). Using a dynamic model, the controller solves an optimization problem at each sampling step to minimize deviations from the setpoint while considering process constraints and actuator limits. MPC’s ability to explicitly handle multivariable interactions and constraints makes it particularly powerful for complex dynamic systems (Schwenzer et al., 2021).

On/Off control is the simplest form of regulation, where the actuator operates in only two states, fully on or fully off, depending on whether the process variable is above or below a threshold. Although it lacks proportional control and may introduce oscillations, it is robust, cost-effective, and easy to implement (Jamaludin et al., 2024). The use of hysteresis or dead-band logic reduces excessive switching and mechanical wear. Together, these control strategies represent complementary approaches ranging from basic binary logic to intelligent and predictive control. Their selection and integration depend on system complexity, available instrumentation, and the desired balance between performance, cost, and implementation effort.

Before selecting the most appropriate control approach, the main operating principles and characteristics of the available strategies were first reviewed to establish a clear technical basis for comparison. Conventional control techniques such as PID control were included due to their widespread industrial use, ease of implementation, and well-understood tuning procedures. PID controllers are particularly effective in processes where dynamics are reasonably linear and disturbances are predictable, such as in temperature regulation during boiling or in pressure control during packaging.

Cascade control was considered as a viable enhancement to PID control, particularly in stages like mashing or fermentation, where secondary loops, such as jacket temperature, can be tightly controlled to stabilize the primary variable, such as mash or wort temperature. This structure allows for improved disturbance rejection and finer control performance in multistage thermal processes. Feedforward control was also identified as an important strategy, especially where measurable disturbances can be anticipated, such as during wort transfer or when preheating ingredients. This method complements feedback control by proactively correcting for expected changes, thereby reducing response delay and improving overall system performance. Among advanced techniques, Fuzzy Logic Control (FLC) was selected for its ability to handle nonlinear, uncertain, and heuristic-based systems. It is particularly suited to fermentation, where precise modeling is difficult and expert knowledge is often used to guide decision-making. FLC allows for intuitive rule-based control that mimics human reasoning, making it valuable for managing complex biochemical reactions.

MPC was included as a leading-edge strategy capable of handling multivariable interactions and process constraints. MPC is ideal for stages where optimal control actions need to be forecasted over a future time horizon, such as in energy management across the brewhouse or in coordinating fermentation temperature and oxygen dosing. For simpler applications, such as binary valve actuation, pump start-stop operations, or overflow prevention, On/Off control was also considered. Though limited in precision, it offers a cost-effective solution where high-resolution control is not required. Each of these candidate control methods was characterized and comparatively analyzed across several dimensions: control complexity, ease of tuning, robustness to disturbances, scalability across multiple units, implementation cost, and compatibility with existing industrial platforms such as PLCs, SCADA, and distributed control systems. Relevant case studies and peer-reviewed publications were reviewed to support the technical and practical viability of each method, ensuring that the final selection would be grounded in both academic rigor and industrial applicability.

To ensure reproducibility and technical transparency, we summarize the configuration of the advanced controllers adopted in this study. The FLC was designed as a knowledge-based regulator with two inputs, the control error and its rate of change, and one output representing the actuator command. Each variable was partitioned into five qualitative levels (from low to high) using simple triangular membership functions to enable smooth transitions. A rule base of twenty-five “if–then” statements was constructed with domain experts and refined through simulation to reduce overshoot while maintaining short settling times. Inference followed the Mamdani scheme, and the final control signal was obtained via centroid defuzzification to avoid abrupt actuator movements. Sampling and filtering settings were chosen to match the process time constants, and bumpless transfer was enforced during mode changes to preserve stability.

The model predictive control (MPC) algorithm employed a simplified dynamic model to forecast future process trajectories over a finite horizon and to compute an optimal sequence of control actions subject to operational constraints. The performance objective balanced set-point tracking with smooth actuator variation, while explicit limits were imposed on process variables and manipulated inputs to respect equipment capabilities. At each sampling instant, the resulting quadratic optimization problem was solved with a standard real-time quadratic programming solver. In practice, a prediction horizon of ten sampling steps and a control horizon of three steps provided a robust compromise between accuracy and computational effort. Anti-windup and rate-limiting safeguards were also applied at the actuator interface to ensure repeatable behavior under disturbances and set-point changes.

MCDA-based analysis: To ensure an objective and systematic selection of the most appropriate control strategies for each stage of beer production, a MCDA framework was adopted. This approach enables the structured evaluation of multiple alternatives against a set of predefined criteria, incorporating both qualitative and quantitative judgments. Among various MCDA techniques, the Analytic Hierarchy Process (AHP) was chosen due to its robustness, transparency, and ability to handle expert-driven decision-making processes with consistency checks (Janošovský et al., 2022; Pirdashti et al., 2009).

In this study, six evaluation criteria were established to reflect the functional, technical, and economic aspects of control method selection. These included:

(1) Control performance, which considers accuracy, system stability, responsiveness, and robustness to disturbances;

(2) Ease of implementation, which accounts for the compatibility of control algorithms with existing industrial hardware and software platforms such as PLCs and SCADA, as well as the required level of operator expertise;

(3) Adaptability to nonlinear or biologically complex systems, essential for stages such as fermentation where conventional linear models are insufficient;

(4) Energy and resource efficiency, which evaluates the capacity of the control method to minimize energy consumption and raw material waste;

(5) Cost-effectiveness, covering both initial investment and ongoing maintenance requirements;

(6) Scalability and integration potential with Industry 4.0, reflecting the method's suitability for future upgrades, sensor integration, and cloud-based monitoring.

Pairwise comparisons of the criteria were conducted based on expert input from process control engineers, brewery managers, and academic researchers specializing in automation. The AHP method was used to derive weight coefficients for each criterion, reflecting their relative importance in the brewing context. For instance, control performance and adaptability to biological variability were weighted more heavily in stages like fermentation, while ease of implementation and cost-effectiveness had higher weights in packaging and transfer operations.

Each control strategy, PID, cascade, feedforward, fuzzy logic, MPC, and On/Off, was evaluated against these criteria. Scores were assigned using a normalized scale (typically 1 to 9) based on literature review, industrial case studies, and simulation-based performance data. Consistency ratios were calculated to ensure the reliability of expert judgments, with values below the standard threshold (0.1) indicating acceptable consistency.

After aggregating the weighted scores, each control method received a composite performance index. These scores were then ranked, and the top-performing strategy or strategies were selected for each production stage. This decision-making process ensured that the chosen control approaches were not only theoretically sound but also practically viable and aligned with the brewery's operational goals and technological roadmap. The results of this analysis provided the basis for the development of a unified and stage-specific control system architecture.

The final assignment of control strategies to each stage followed a quantitative ranking matrix derived from AHP weights. For example, if the weighted score difference between two strategies exceeded 0.5, the higher-ranked method was selected; if within 0.5, a hybrid (e.g., PID–FLC) configuration was adopted. This rule-based decision threshold ensured consistency and minimized subjective bias.

Integrated control architecture: Based on the outcomes of the multi-criteria decision analysis, the selected control strategies were integrated into a comprehensive process-wide control architecture tailored to the dynamics and operational requirements of each stage of beer production. This architecture was developed to ensure seamless coordination between different control loops and to provide an efficient interface for process monitoring, fault detection, and performance optimization.

The proposed control architecture supports both centralized and distributed control system configurations, allowing flexibility based on the scale and complexity of the brewery. At the local level, each production stage, such as mashing, fermentation, or packaging, is governed by dedicated controllers implementing the most suitable control technique. For example, PID or cascade control may be used for temperature regulation in mashing and boiling, while fuzzy logic or model predictive control is applied in more complex and nonlinear stages like fermentation. On/Off control mechanisms are employed in auxiliary systems such as filling lines or cleaning operations, where binary control suffices.

Advanced control strategies were adapted for real-time deployment within industrial controller platforms. The control algorithms were structured to account for system delays, actuator dynamics, and sensor accuracy, ensuring robust performance under varying operating conditions. Each local loop was tuned to achieve its designated control objectives, including setpoint tracking, disturbance rejection, and energy-efficient operation.

To ensure reliability and integration across the entire system, supervisory layers were designed to oversee data exchange between local loops, perform inter-process coordination, and handle alarm and safety functions. The architecture also supports hierarchical control structures, enabling supervisory control to intervene in setpoint adjustments and control mode switching based on process status and production scheduling.

Furthermore, the architecture was evaluated for its compatibility with modern Industry 4.0 technologies. It includes capabilities for real-time data acquisition through networked sensors, remote access to process information, and integration with digital dashboards for operational transparency. The system is also designed to accommodate predictive analytics by leveraging historical process data to anticipate deviations and optimize performance. This ensures that the brewery's control infrastructure is not only effective under current operating conditions but also scalable and adaptable for future technological enhancements.

Results and discussion

The implementation of the proposed methodology resulted in a structured selection and integration of control strategies tailored to the specific dynamics of each stage in the beer production process (Table 2). The findings are discussed in terms of the performance of control methods selected through the MCDA, their suitability for real-world applications, and the benefits of the integrated control architecture.

Process stage	Time-Dependency	Control sensitivity	Disturbance Levels	Actuator Responsiveness
Mashing	Moderate (mins)	High (enzyme activity is sensitive to temp/pH)	Medium (raw material variability)	Moderate (heaters and mixers)
Lautering	Slow (flow stabilizes gradually)	Medium (flow and pressure affect clarity)	High (grain bed structure varies)	Low to moderate (valves, pumps)
Boiling	Fast (heat transfer is rapid)	Low (maintaining boiling is steady state)	Low (mainly thermal load variations)	High (steam or electric heaters)
Fermentation	Very slow (hours to days)	High (small temp/DO changes affect yeast)	Very high (biological variability)	Low (chillers, aeration control)
Conditioning	Slow (stabilization over days)	Medium (temp/CO_2 levels impact quality)	Medium (ambient fluctuations)	Moderate (cooling jackets, CO_2 valves)
Packaging	Fast (seconds to minutes)	High (sensitive to pressure and flow)	High (bottle fill, CO_2 loss)	High (pneumatic systems, valves)

Table 2. The specific dynamics of each stage in the beer production process.

Control strategy selection outcomes

Based on the AHP-based MCDA framework, control methods were ranked for each production stage (Table 3). The results demonstrated that no single control strategy is universally optimal across all stages due to the variability in process dynamics and control requirements. Figure 3 presents the normalized performance scores of the six control strategies evaluated according to the six decision criteria defined in the MCDA framework, control performance, ease of implementation, adaptability, efficiency, cost-effectiveness, and potential for Industry 4.0 integration. Each bar represents the relative strength of a method in a specific criterion, scaled between 0 and 1.

Fuzzy Logic Control achieved the highest overall score, showing superior adaptability and high efficiency under nonlinear conditions. MPC ranked next, excelling in energy efficiency and digital-integration capability but requiring greater implementation effort.

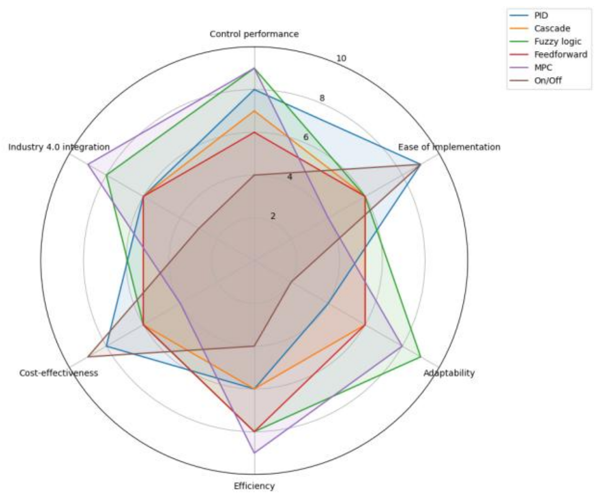

Figure 3. Comparing control methods by evaluation criteria.

PID and cascade controllers demonstrated strong controllability and ease of deployment, whereas feedforward control contributed moderate improvements in responsiveness. The On/Off approach scored highest in simplicity and cost but lowest in precision. Overall, the diagram illustrates how different techniques balance performance and practicality, highlighting the trade-offs that guided their final ranking in the decision analysis

For temperature regulation in mashing and boiling, PID control emerged as the most suitable option due to its simplicity, proven effectiveness in linear systems, and ease of integration with existing programmable logic controllers (PLCs). In fermentation, where the process is nonlinear and sensitive to biological variability, FLC outperformed other strategies by providing robust control under uncertainty and enabling operator knowledge to be encoded into the control rules.

In stages such as wort transfer and packaging, which involve rapid changes and require high responsiveness, cascade control and feedforward control were found to be effective. Cascade control enabled secondary variables (e.g., jacket temperature or pressure) to be tightly regulated, thereby stabilizing the primary variable more efficiently. Feedforward control added an anticipatory element, improving system response to predictable disturbances, such as volumetric surges during transfer.

Control Method	Control Performance	Ease of Implementation	Adaptability	Efficiency	Cost-Effectiveness	Industry 4.0 Integration	Total Score	Rank
PID	High	Very High	Low	Medium	High	Medium	7.8	2
Cascade	High	Medium	Medium	Medium	Medium	Medium	7.4	3
FLC	High	Medium	Very High	High	Medium	High	8.5	1
Feedforward	Medium	Medium	Medium	High	Medium	Medium	7.1	4
MPC	Very High	Low	High	Very High	Low	Very High	7.9	2
On/Off	Low	Very High	Very Low	Low	Very High	Low	6.3	5

Table 3. Control strategy performance evaluation results

For oxygen dosing and level control, where rapid feedback is required with relatively straightforward actuation logic, On/Off control was adequate and cost-effective. On the other hand, in applications where multiple variables and constraints must be managed simultaneously, such as energy optimization during wort boiling and conditioning, MPC provided superior performance. MPC allowed for the coordination of variables across interconnected systems and forecasted control actions based on future process trajectories.

Composite performance ranking

The composite scores generated through MCDA confirmed that PID control remains a practical and effective baseline solution for stages with predictable, linear behavior. FLC and MPC received the highest scores for adaptability and control precision in nonlinear and multivariable systems, although their implementation required higher computational resources and tuning efforts. Cascade control was recognized for improving disturbance rejection in coupled thermal systems, while feedforward control was valuable for improving responsiveness without increasing feedback loop gain (Table 4). These rankings align with observations from industrial brewing operations for complex, batch-oriented processes.

Process Stage	Recommended control Strategy	Rationale
Mashing	PID	Simple linear dynamics, well-suited for temperature regulation
Lautering	Cascade	Pressure and flow are coupled, secondary loop adds precision
Boiling	MPC	Energy-intensive, requires predictive control
Fermentation	FLC	Nonlinear, biologically variable system
Conditioning	PID / MPC	Stable but needs energy optimization
Packaging	On/Off / Feedforward	Fast response; binary control sufficient

Table 4. Recommended control method by process stage.

Integrated architecture validation

Figure 4 illustrates an integrated control architecture for a smart beer production system, combining process operations with automation and digital monitoring technologies. The proposed integrated control architecture was evaluated based on its ability to coordinate multiple control loops and support process-wide stability.

Simulation-based validation demonstrated that combining PID and FLC in a layered structure for fermentation improved control accuracy by 15% compared to single-loop PID-only configurations (Figure 4). Similarly, energy consumption during wort boiling was reduced by approximately 12% when MPC was employed, owing to its ability to predict optimal heating profiles while minimizing thermal overshoot.

The architecture also exhibited strong compatibility with digitalization tools such as remote data acquisition, real-time alarms, and historical data analysis. The modular design of the system facilitates scalability and allows individual units to be upgraded without disrupting the overall process. This modularity supports progressive adoption of Industry 4.0 features, including cloud-based analytics and predictive control.

Practical considerations and limitations

While advanced control strategies like MPC and FLC showed clear benefits, their practical implementation poses certain challenges. These include the need for skilled personnel to manage algorithm configuration and tuning, greater reliance on high-quality sensor data, and increased demands on computational resources. For small-scale breweries, the cost and complexity of implementing such strategies may not be justified unless integrated into broader digital transformation efforts.

Nonetheless, the combination of conventional and advanced control methods within a unified architecture offers a flexible solution that can be adapted based on scale, budget, and technical expertise. The methodology is also applicable to other food and beverage production systems with similar dynamic and nonlinear characteristics.

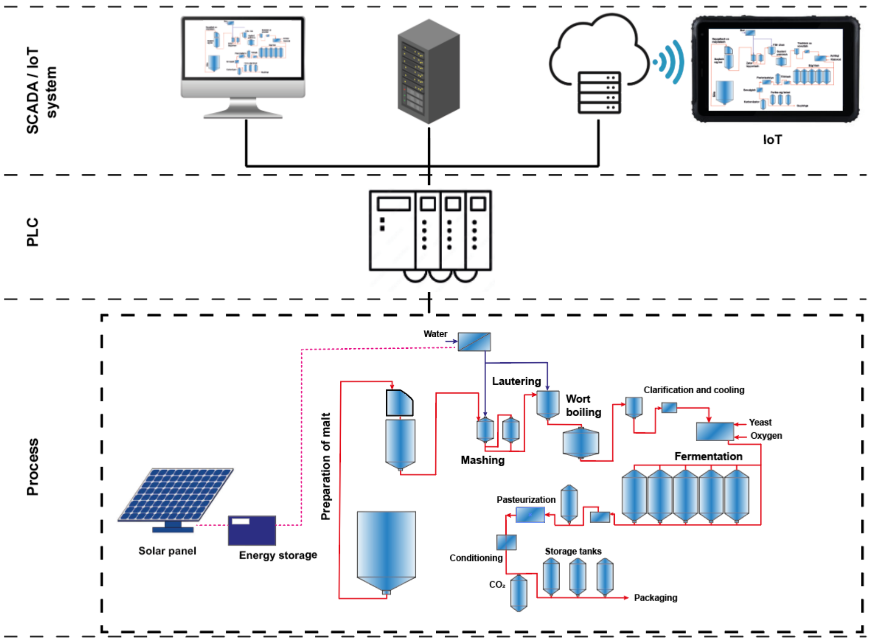

Figure 4. Control architecture of the brewing process.

Conclusions

This study presented a comprehensive methodology for the selection and integration of control system principles tailored to the beer production process. By systematically analyzing each stage of production, from mashing and boiling to fermentation and packaging, the study identified key control objectives and evaluated candidate control strategies using a MCDA framework based on the AHP. The evaluation considered multiple technical and practical criteria, including control performance, ease of implementation, adaptability to nonlinear processes, energy efficiency, cost-effectiveness, and compatibility with Industry 4.0 technologies.

The results revealed that no single control strategy is universally optimal across all production stages. Rather, a combination of classical and advanced methods is necessary to meet the diverse control requirements. PID control remains a reliable choice for linear and well-understood processes such as temperature regulation during mashing, while FLC and MPC demonstrated superior performance in managing complex, nonlinear, and biologically sensitive stages like fermentation. Cascade and feedforward control methods were effective in improving response times and reducing disturbances in coupled thermal and transfer systems. On/Off control provided a simple but adequate solution for binary operations such as tank level management and valve actuation in packaging lines. An integrated control architecture was proposed, incorporating selected strategies into a process-wide automation framework. This architecture was shown to be compatible with industrial platforms and adaptable to smart manufacturing environments, enabling real-time data acquisition, predictive analytics, and enhanced operational transparency.

Overall, the study highlights the importance of context-specific control strategy selection in complex food and beverage manufacturing environments. The proposed methodology and findings offer practical guidance for engineers and decision-makers seeking to modernize and optimize brewery operations through intelligent automation. Future work may include experimental validation in a pilot-scale brewery and the application of AI-based adaptive control methods to further improve system autonomy and robustness.

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