Research on Neural Network Temperature Control Algorithm in Wine Brewing

Wang Laizhi[1,2*], Zhang Erbing[1], Feng Liyi[1]
[1]Chongqing City Management College, Chongqing, China
[2]Intelligent Robotics Control and Interaction Engineering Research Center of Chongqing Education Commission of China, Chongqing, China
**Corresponding Author.*

Abstract: Baijiu brewing is an old craft, but it still lives and dies by one very modern thing: temperature control. When fermentation or distillation drifts off target, the result is familiar to anyone in a distillery—uneven quality, lower yield, and more steam and electricity burned than necessary. In many plants, temperature is still managed mainly by experience, which can be effective but also inconsistent and slow to respond. This paper examines neural-network-based temperature control for baijiu production. We sort out which temperature variables matter most in practice, build control rules around them (with the necessary mathematical expressions), and test the method against standard PID control. The PID baseline works, but the neural-network approach shows clearer gains in stability and performance in our comparison, and the experiments suggest it can be implemented on real equipment. Future work will focus on improving model tuning, making the control logic easier for operators to understand, and applying the approach across connected stages rather than optimizing each step separately.

Keywords: Baijiu Brewing; Temperature Control; Neural Network; Wine Body Quality

1. Introduction

Baijiu is one of China's signature spirits, and it's also one of the easiest to mess up if the temperature isn't steady. Temperature shapes microbial activity, raw-material conversion, and, downstream, aroma and taste. During fermentation and distillation, temperature swings don't just change "how fast" things happen—they can change what gets produced. In sauce-flavored baijiu in particular, where the process often runs at higher temperatures, control mistakes tend to show up loudly in the final flavor.

In real production, temperature is often adjusted manually. That hands-on approach carries a lot of hard-won know-how, but it also brings subjectivity and delay. By the time a human notice a drift and corrects it, the system may already have moved on, and the result is larger temperature fluctuations than the process can comfortably tolerate. Those fluctuations can reduce distillation yield, degrade liquor quality, and increase energy use, which clashes with the push toward greener brewing.

This study develops a neural-network-based temperature control method. We use sensor data to build a dynamic model, then use prediction plus closed-loop control to keep temperature closer to where it should be. The goal is simple and production-focused: higher yield, more consistent quality, and less wasted energy, with a practical reference for intelligent upgrades in brewing lines [1–3].

2. Analysis of Temperature Control Mechanism in Baijiu Brewing Process

Baijiu brewing is a complicated biochemical system, and temperature is the main variable that steers both material conversion and flavor formation [4–5]. Different stages need different kinds of control. Some steps want a tight setpoint, others need stable heating curves, and fermentation adds its own heat generation on top of everything else.

Raw material processing starts with steaming. The process typically targets about 100C to drive starch gelatinization, which sets up the later saccharification and fermentation steps. Too low, and gelatinization is incomplete; too high for too long, and you can damage quality while also wasting energy. There's also a hygiene benefit at higher temperatures, so the "best" temperature isn't only about conversion—it's also about controlling contamination risk.

Qu-making (starter cultivation) is one of the biggest flavor levers in baijiu. Temperature here acts like a selection pressure: it decides which microbes dominate. High-temperature Qu-making (often above 60C) is used for sauce-flavored baijiu and supports the formation of key precursors. Moderate-temperature methods, used in other aroma types, support different microbial structures, including growth conditions favorable to Aspergillus.

Fermentation is where ethanol and many flavor compounds are formed, and temperature is the variable that most directly governs yeast activity and conversion efficiency [6–7]. If temperature control is sloppy, the effects aren't subtle: fermentation rate shifts, metabolite profiles change, and ester formation can move in the wrong direction. In other words, temperature stability is not a "nice to have"—it's part of the recipe.

Fermentation usually runs around 20–35°C, and that temperature band doesn't just keep the process moving—it changes where a lot of key flavor compounds "settle" chemically. Different aroma styles also use noticeably different temperature profiles, and those differences steer which microbes show up first, which ones take over later, and what kinds of flavors you end up with [8–9].

Distillation is the step where you physically separate and clean up what fermentation produced. Here, temperature control is basically quality control: if you can't hold the right temperatures at the right moments, the final liquor suffers. In segmented distillation, you split out groups of compounds across specific temperature ranges. When temperature is managed tightly, it's easier to cut fractions cleanly and keep impurities under control. Done well, it can also save energy, because you're not overheating or running longer than you need.

Aging is mostly about time, but temperature still matters more than people like to admit. Keeping storage temperatures steady helps the liquor mature and build complexity [10–11]. Big swings in temperature can push aging in the wrong direction and drag down overall quality.

3. Design of Temperature Control Algorithm Based on Neural Networks

3.1 Neural Network Model Selection

Baijiu brewing data is messy in the way real processes are: it's time dependent, nonlinear, and full of variables that affect each other. Long Short-Term Memory (LSTM) networks handle that kind of sequence behavior well, so they're a solid choice for temperature prediction. This work focuses on LSTM and also tests whether a CNN–LSTM hybrid can do better in practice [12].

3.2 Network Structure Design

The model uses either a sequence-to-single-point or sequence-to-sequence setup. As shown in Figure 1, it has an input layer, an LSTM recurrent layer [13], a fully connected layer, and an output layer.

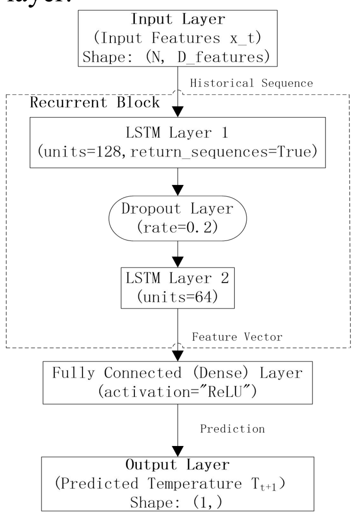

Figure 1. Network Topology Structure

4. Experimental Design and Performance Evaluation

4.1 Performance Evaluation System

Baijiu brewing is complicated enough that a single metric doesn't tell you much. So, we built an evaluation framework that looks at three things: (1) process control performance, (2) production economics, and (3) final product quality. Taken together, these measures give a fuller picture of how well a control algorithm works, including how the system responds over time, what it costs to run, and what you end up delivering to the consumer.

4.2 Experimental Design and Analysis Methods

To make the results trustworthy—and to keep this from turning into a "too many moving parts" comparison—this study uses a parallel, side-by-side design that sticks to a single-variable rule: the temperature control strategy is the only thing that changes.

4.2.1 Experimental Grouping

Three groups are run in parallel. Everything else is kept the same as much as realistically possible: raw materials from the same batch, the same fermentation and distillation equipment (same model and specs), and the same workshop environment. The point is to squeeze down confounders so any differences we see can be traced back to the control method [14].

Experimental group (NN-based)

This is the main group of interest. It uses the neural-network temperature control algorithm proposed in this paper.

Control group A (PID)

This group uses a standard PID controller (Kp, Ki, Kd), which is still the default in a lot of industrial temperature control setups. For a fair fight, the PID parameters will be tuned with classic engineering methods (for example, Ziegler–Nichols) so the controller is performing as well as a competent mainstream implementation can.

Control group B (empirical/manual)

This group relies on manual temperature control by experienced winemakers, based on judgment and hands-on operation rather than an automated algorithm. It acts as a "traditional practice" baseline, so we can put a number on what the intelligent controller adds beyond human experience alone.

4.2.2 Data Collection and Statistical Analysis

A high-precision automated acquisition system will run for the full experiment. Platinum resistance temperature sensors and online infrablue CO analyzers will record key process parameters in the fermentation tanks and distillation vessels at a fixed sampling interval (for example, every 5 minutes), building a batch-level process dataset.

After each batch is finished, standardized product samples will be collected and sent to a qualified lab for physicochemical testing and sensory evaluation.

For analysis, quantitative data will be processed in statistical software (for example, SPSS or Python with SciPy). Differences between groups will be tested with an independent-samples t-test when comparing two groups, or one-way ANOVA when comparing all three groups. The significance threshold will be set at $\alpha = 0.05$.

Results will be shown with plots that make the comparisons easy to read: temperature control curves, radar charts for flavor compounds, and bar charts for the main performance metrics. These figures are used to show not just whether one strategy wins, but where the gaps come from.

5. Experimental Results

5.1Experimental Design and Multidimensional Data Collection

We used a concurrent, multi-batch parallel comparison design and built a real-time, multi-parameter data acquisition setup to keep the experiment defensible and the results repeatable.

Experimental subjects and groups. The work targeted two core stages of strong-aroma baijiu production: solid-state fermentation (medium-temperature daqu) and distillation/purification. Each run was split into three parallel groups:

- Baseline control: manual control based on experienced winemakers' judgment
- Traditional control: PID control with tuned parameters
- Experimental group: neural-network intelligent control using LSTM and CNN-LSTM models

All groups used the same raw materials, recipe and equipment configuration.

Fermentation data collection. Solid-state fermentation varies a lot across both time and position in the pit/tank, so we treated it like a 3D temperature problem rather than a single probe reading. High-precision thermocouple arrays were installed at multiple depths and locations in the fermentation tank to capture the temperature field. In parallel, online sensors tracked key real-time process indicators, including CO2 concentration (used here as a proxy for fermentation intensity) and pH (acidity). We also took periodic samples to measure alcohol content and residual sugar. Data were logged every 15 minutes across the full fermentation cycle (about 7–14 days).

Distillation data collection. Distillation changes fast, so the sampling interval was shortened to every 5 minutes. We monoblue pot temperature, steam pressure, distillate outlet temperature, and alcohol degree. These signals were used to control the timing of head cutting and tail removal.

Energy use and quality evaluation. Steam and electricity consumption were recorded separately for each batch during heating and cooling. Finished spirits were analyzed for key flavor compounds (esters, alcohols, aldehydes, acids) by GC-MS, then evaluated with blind sensory testing by a qualified panel. We used these results to calculate alcohol yield and total energy consumption.

5.2 Quantitative Presentation of Experimental Results

Temperature control accuracy and dynamic behavior.

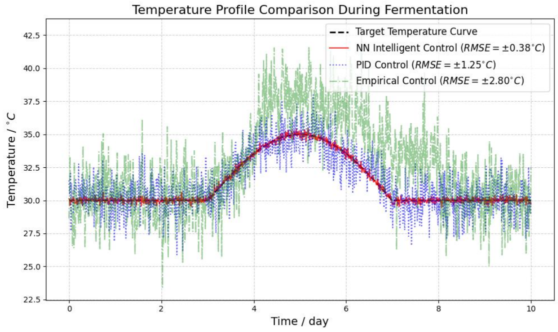

Figure 2. Comparison of Temperature Curves During Fermentation Process

As shown in Figure 2, the neural-network (NN) control group achieved the lowest temperature-tracking error (RMSE) compablue with both the PID group and the experience-based baseline group. The bigger story, though, showed up during peak microbial heat generation: the NN controller scheduled cooling earlier and kept temperature swings inside the target band. That matte blue because it blocked secondary temperature rise (STR), which is one of the easiest ways to knock aroma quality off course when fermentation gets jumpy.

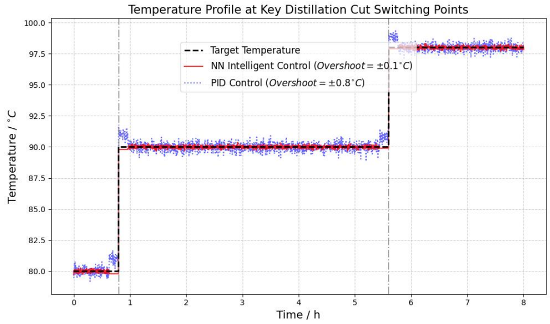

Figure 3. Comparison of Peak Temperature Curves

Figure 3 compares the temperature curves during distillation. In the purification stage, the neural network (NN) controller reacts quickly (about 0.1 °C) and shows little overshoot at the key cut points (heads to heart, and heart to tails). In plain terms: the cuts are cleaner, the boundaries are clearer, and you get less mixing between low boiling and high boiling impurities.

Wine quality and sensory evaluation results are listed in Table 2.

Table 1. Comparison of Sensory Evaluation Scores

evaluative dimension	Empirical control group (mean)	PID control group (equal distribution)	NN Intelligent Control Group (mean)	Improvement rate compared to the PID group
Aroma intensity	80.5	83.2	86.5	↑3.97%
flavor harmony	79.8	82.5	87.2	↑5.69%
Total score	80.5	82.8	86.9	↑4.95%

Table 2 shows that, across multiple batches, the NN control group has much lower batch to batch variation than the PID group (about 30% lower standard deviation across the quality indicators). That's the part I care about most, honestly: not just a higher score once, but results you can repeat without crossing your fingers.

6. Conclusion

This study applies a neural network-based temperature control method to baijiu brewing. The experiments show improvements in yield, liquor quality, and energy use. Fermentation temperature fluctuations were held within 0.38 °C. Alcohol yield per unit of raw material increased by 10.20%, while overall energy consumption dropped by 12.64%. Total ester content increased by 10.98%, and higher alcohols decreased by 17.33%. Taken together, these results point to a practical route for upgrading brewing control toward more automated, consistent production.

Acknowledgments

This paper is supported by the project of Science and Technology Research Program of Chongqing Municipal Education Commission of China(No.KJQN202303313, KJQN202403322，KJQN202503319).

References

[1]Yu Zihan, Li Qingliang, Lu Yanxiang, et al. Research progress on automated and digital brewing processes for white liquor[J]. China Brewing. 2025,44(11):7-14.

[2]Li Xianshu, Wang Yongzhong, Wu Junlong, et al. Feasibility study on brewing sauce-flavor liquor with high-temperature daqu in Xinjiang Yili [J]. Brewing. 2025,52(06):81-84

[3]Li Shenlong. Research on Development Trends of Intelligent Brewing Robots for Baijiu Based on Patent Big Data [J]. Robotics Technology and Applications. 2025(05):2-9.
[4]Zhang J, Li YJ. Investigation on the Influence and Regulation of Temperature in Baijiu Brewing [J]. Food Safety Guide. 2021(28):165-166.
[5]Jiang Xue, Su Yuanyuan, Cang Yipeng, et al. Research progress on the effects of fermentation temperature on Daqu and strong-aroma baijiu fermentation processes [J]. Brewing Science and Technology. 2025(08):106-110.
[6]Wang XP. Influence and Control of Temperature in the Brewing Process of Strong Aroma Baijiu [J]. Brewing Science and Technology. 2018(06):88-90.
[7]Zhang Xiaoming, Wu Dingchun, Yang Yi, et al. Research on Temperature Control of Winter Pit Loading of Fermented Grains in Mechanical Air-Drying Process for Strong Aroma Baijiu [J]. Brewing Science and Technology: 1-13.
[8]Liao Qian. Research on Quality Grading and Blending Ratio Model for Small Qu Fragrant Type Baijiu Base Liquor [D]. Yunnan Agricultural University, 2024.
[9]You Xiangtao. Key Technologies and Quality Characteristics of Baihe Multi-grain Baijiu Brewing [D]. Jishou University, 2023.
[10]Hu Haicheng. Research on Online Segmentation and Reassembly Methods of Baijiu Based on Refractive Principles and Spectral Analysis [D]. Hebei University of Technology, 2023.
[11]Xue Yuan. Research on Wine Extraction Equipment Based on Hops Image Classification for Baijiu [D]. Hebei University of Technology, 2021.
[12]Li Pengbo. Research on Intelligent Wine Harvesting System Based on Baijiu Quality Grading [D]. Hebei University of Technology, 2021.
[13]Yang YQ. Construction of a solid-state simulated fermentation system for baijiu and microbial community structure analysis during pile-up and pit fermentation of sauce-flavored baijiu [D]. Fujian Normal University, 2015.
[14]Huang Xiaofeng. Research on Intelligent Blending System for China Distilled Spirits [D]. Zhejiang University, 2014.

