DEVELOPMENT OF AN AUTOMATION AND INTELLIGENT CONTROL SYSTEM FOR THE POLYVINYL CHLORIDE DRYING PROCESS

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Abstract. Drying is one of the most energy-intensive and quality-sensitive operations in suspension polyvinyl chloride (S-PVC) production. The process is characterized by nonlinear heat- and mass-transfer dynamics, long transport delays, changes in feed moisture, grade-dependent particle properties, and strict limits on final resin moisture and thermal exposure. This paper proposes a hierarchical automation and intelligent-control architecture for PVC drying that combines conventional regulatory control with online moisture estimation, model-predictive optimization, fuzzy supervisory logic, and data-driven soft sensing. The proposed system is organized around a pneumatic pre-drying stage and a fluidized-bed finishing stage, although the same principles can be adapted to single-stage units. Key controlled variables are outlet moisture, bed/material temperature, pressure drop and energy demand, while manipulated variables include thermal duty, drying-air flow, feed rate and residence time. Literature on PVC drying shows that inlet air temperature is a dominant operating factor and that pneumatic pre-drying can substantially reduce energy use. Evidence from advanced industrial drying control further supports the use of MPC, fuzzy control and neural-network models for disturbance rejection and moisture stabilization. The resulting concept is intended to improve product consistency, reduce over-drying, lower specific energy consumption and provide a practical basis for implementation in a PLC/DCS-SCADA environment.

Keywords: polyvinyl chloride, PVC drying, fluidized bed, pneumatic dryer, automation, model predictive control, fuzzy logic, soft sensor, intelligent control.

INTRODUCTION

Suspension polyvinyl chloride is produced as a water-based slurry and therefore requires mechanical dewatering followed by thermal drying before storage, compounding and downstream processing. After centrifugation, the product is a wet porous cake whose residual water must be removed without compromising particle morphology, bulk properties or thermal stability. Industrial PVC drying commonly combines pneumatic transport drying with a fluidized-bed finishing step. Experimental and modeling work on PVC powder has reported wet-cake moisture in the range of approximately 0.20–0.35 kg water per kg dry PVC after centrifugation, while the final stage is required to reduce residual moisture to a low level suitable for product specification (1). The same work indicates that drying can require roughly 800–1500 kJ per kilogram of dry PVC depending on operating conditions and resin grade, which makes the section an important target for energy optimization (1).

The control problem is more difficult than simple temperature regulation. PVC drying is a coupled gas-solid operation involving convection, particle-scale diffusion, hydrodynamics, solids residence time and humidity-dependent driving forces. Aubin et al. showed that both external and internal mass-transfer resistances influence drying kinetics and identified inlet air temperature as a particularly influential operating variable (1). A later experimental and numerical study of S-PVC pre-drying demonstrated that the energy demand of the overall drying system can be reduced by using a pneumatic dryer upstream of the fluidized bed; the reported specific-energy reduction was about 23.1% for the investigated

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configuration (2). These observations support the development of a control system that regulates not only temperature but also moisture, airflow, feed conditions and energy use.

Conventional industrial dryers are frequently operated with independent PID loops and operator-set targets. This structure is robust and understandable, but it does not directly account for multivariable interactions, dead time, nonlinear moisture kinetics or changing disturbances. Modern drying literature therefore increasingly combines mechanistic models, computational fluid dynamics (CFD), model predictive control (MPC), fuzzy logic and data-driven estimators. General industrial drying references emphasize that energy efficiency and cost reduction depend on coordinated equipment design and operating strategy (3), while CFD has become an established tool for evaluating gas-solid transport and thermal fields in complex dryers (4). The objective of this paper is to develop a technically feasible automation and intelligent-control concept for PVC drying that can be implemented incrementally in a real production environment.

MAIN PART

Technological characteristics of the PVC drying process

A typical suspension-PVC line first removes bulk water mechanically, then sends the wet cake to a thermal drying section. In a pneumatic pre-dryer, high gas velocity provides intensive heat and mass transfer over a short contact time. The partially dried particles can then enter a fluidized-bed dryer, where longer residence time and strong particle mixing enable final moisture equalization. Banooni et al. reported an industrial reference case in which centrifuged S-PVC cake contained about 23% moisture and the existing fluidized-bed system produced material near 0.2% outlet moisture; they further demonstrated the potential of upstream pneumatic pre-drying for reducing specific energy use (2). The exact set points are plant- and grade-specific, so an automation system should treat moisture and thermal limits as recipes rather than fixed universal constants.

Table 1. Main process variables for automation of PVC drying

Variable group	Typical measurements / variables	Control significance
Quality outputs	Outlet PVC moisture; product temperature; moisture variability	Primary quality targets; indicate under- or over-drying
Thermal state	Inlet/outlet air temperature; bed temperature; heater duty	Determines drying potential and thermal exposure
Gas phase	Air flow; relative/absolute humidity; pressure; exhaust temperature	Defines heat/mass-transfer driving force and fan load
Solids flow	Feed rate; initial moisture; residence time; bed inventory	Major disturbances and production-capacity constraints
Hydrodynamics	Bed pressure drop; fan pressure; cyclone/filter differential pressure	Indicates fluidization quality, blockage and solids entrainment
Manipulated inputs	Steam/heater valve, fan VFD, feed screw speed, recycle/bypass damper	Actuators used to regulate moisture, temperature and energy

The thermal and moisture dynamics exhibit different time scales. Air temperature responds relatively quickly to heater or steam-valve movement, whereas the measured outlet moisture responds

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after transport and residence-time delays. This mismatch can lead to oscillation if a single fast PID loop is tuned aggressively. In addition, feed moisture and ambient humidity may vary substantially even when production rate is constant. The proposed control philosophy therefore separates fast regulatory loops from a slower supervisory optimization layer.

Functional structure of the proposed automation system

The proposed architecture is hierarchical. At the field level, temperature, humidity, flow, pressure, differential-pressure and moisture sensors provide continuous measurements. Variable-frequency drives regulate fans and feed screws, while control valves regulate steam or another heat-transfer medium. A PLC or DCS executes fast safety interlocks and conventional regulatory loops. Above this level, an intelligent supervisory controller estimates unmeasured states, predicts future outlet moisture and computes economically efficient set points. The SCADA/historian layer stores process trajectories for model updating, alarm analysis and performance monitoring.

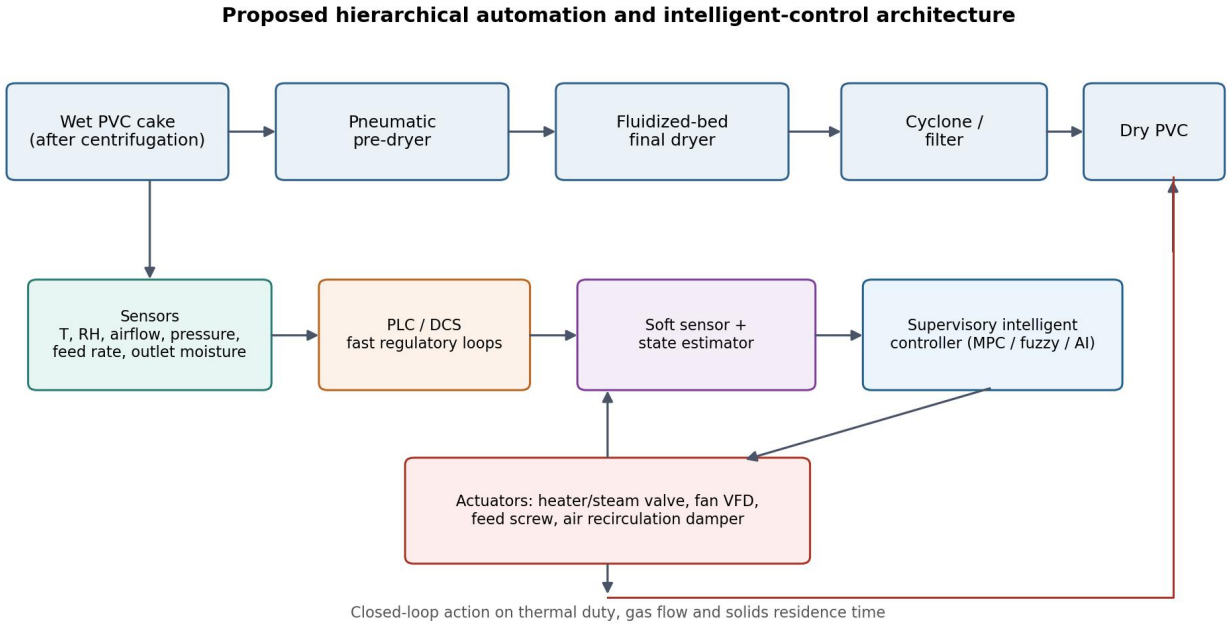


Figure 1. Proposed hierarchical architecture for automated and intelligent control of PVC drying.

The structure deliberately preserves conventional control as the inner layer because basic loops must remain deterministic, transparent and fail-safe. The intelligent layer does not replace the PLC/DCS; instead, it supplies optimized set points or bias corrections. Such a division is consistent with industrial MPC practice, where an advanced controller coordinates several interacting variables while low-level loops track the commanded values. Earlier work on industrial dryers showed that MPC can outperform traditional temperature-only control by explicitly controlling an inferred moisture state and periodically updating the process model (5).

Online moisture estimation and intelligent soft sensing

Reliable real-time outlet moisture measurement is the central requirement for closed-loop quality control. If a plant-grade online moisture analyzer is available, it should be used as the principal quality sensor. However, analyzers may have maintenance requirements, sampling delays or sensitivity to particle presentation. For this reason, the system should include a soft sensor that estimates moisture from secondary measurements such as inlet and outlet temperature, exhaust humidity, airflow, feed rate,

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bed pressure drop and recent actuator history. The estimator can be implemented as a first-principles state observer, a regression model, an artificial neural network or an LSTM model for time-dependent data.

The soft sensor must be trained and validated on plant data covering normal grades, seasonal ambient conditions, start-ups and throughput changes. It should also include plausibility limits and drift detection. The role of AI is therefore not to provide an unconstrained black-box command but to improve state estimation and prediction under a supervisory safety envelope. Modern deep-learning MPC research in industrial drying has demonstrated that neural-network surrogates can substantially accelerate predictive calculations while retaining useful moisture-prediction accuracy, although such results were obtained for paddy drying and should be transferred to PVC only after dedicated validation (8).

Model predictive and fuzzy supervisory control

For the principal moisture-control task, MPC is appropriate because it explicitly handles multivariable coupling, delays and operating constraints. At each control interval, the model predicts future outlet moisture and temperatures over a finite horizon. The optimizer then selects a sequence of heater duty, gas-flow and, when allowed, feed-rate adjustments. A simplified objective function can be written as $J = \Sigma[wM(Mout - Msp)^2 + wE \cdot E + w\Delta u(\Delta u)^2]$, where Mout is predicted outlet moisture, Msp is the grade-specific target, E is thermal/electrical energy demand and Δu represents actuator movement. Hard constraints can be imposed on thermal exposure, fan limits, bed pressure drop and production rate.

A fuzzy supervisory layer can complement MPC during operating regions where an accurate model is difficult to maintain, for example start-up, rapid grade transition or abnormal feed-moisture excursions. Fuzzy logic is well suited to nonlinear drying because it can encode operator knowledge in rules such as "if outlet moisture is high and exhaust humidity is rising, increase thermal duty moderately unless bed temperature is near its limit." Studies on industrial dryers have shown that self-tuning fuzzy or fuzzy-PID strategies can improve control of nonlinear and time-varying drying systems compared with fixed conventional tuning (6). Neural-network-based predictive control has likewise been successfully applied to drying processes with measurable improvements in moisture stability (7).

Table 2. Recommended hierarchy of control functions

Layer	Main function	Typical algorithm	Update speed / role
Safety / interlock	Protect equipment and product	Hard logic, permissives, trips	Fastest; independent of optimization
Regulatory	Track temperature, flow and pressure set points	PID / cascade PID	Seconds
State estimation	Estimate outlet moisture and hidden states	Observer, regression, ANN/LSTM	Seconds to minutes
Supervisory quality control	Stabilize product moisture	MPC; fuzzy gain scheduling	Minutes / residence-time scale
Economic optimization	Minimize energy while meeting quality limits	Economic MPC / supervisory optimizer	Slow supervisory layer
Performance	Detect drift, fouling and	SPC, residual analysis,	Historian / maintenance

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Layer	Main function	Typical algorithm	Update speed / role
management	sensor faults	anomaly detection	horizon

Energy-efficiency criterion and control targets

The intelligent controller should avoid the common strategy of maintaining excessive inlet temperature simply to protect against wet-product excursions. This practice reduces moisture variability at the cost of over-drying, unnecessary heat consumption and possible deterioration of heat-sensitive resin. Instead, the controller should maintain outlet moisture close to the required specification with minimum feasible thermal input. Energy minimization must remain subordinate to product quality and safety constraints.

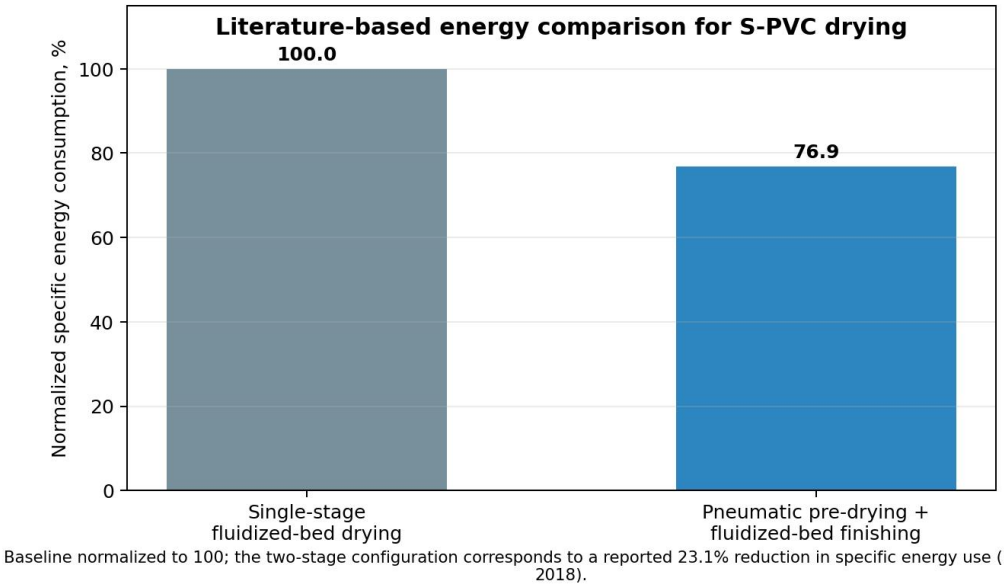


Figure 2. Normalized specific-energy comparison based on the S-PVC pre-drying study of Banooni et al. (2).

Figure 2 is not a new experimental result; it reformats the literature-reported 23.1% reduction in specific energy consumption for the studied two-stage concept, taking the original single-stage case as a normalized baseline of 100 (2). The result illustrates why a control system should coordinate the pneumatic and fluidized-bed sections rather than optimize each unit independently. The upstream section can remove moisture efficiently at high driving force, while the finishing section provides final stabilization and quality equalization.

Instrumentation and implementation requirements

A practical implementation should prioritize measurement quality before introducing advanced algorithms. Temperature sensors should be installed at dryer inlets, outlets and representative bed zones; air flow and humidity should be measured on both supply and exhaust streams; differential pressure should be monitored across the fluidized bed, cyclone and filters; and feed mass flow should be measured or inferred from a calibrated feeder. The outlet-moisture analyzer requires a stable sampling geometry and periodic laboratory verification. All critical instruments should have diagnostic status available to the PLC/DCS and historian.

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The model-development phase can use plant historians together with controlled step tests that remain within approved operating limits. CFD and mechanistic models are valuable for identifying important zones, sensor locations and plausible interactions, but the online controller usually requires a reduced-order model. CFD reviews emphasize that detailed Eulerian-Eulerian or Eulerian-Lagrangian descriptions are powerful for dryer design and understanding, whereas their computational burden often makes them unsuitable for direct real-time optimization (4). Accordingly, the proposed system uses high-fidelity models offline and compact dynamic models online.

Table 3. Suggested implementation sequence for an industrial PVC line

Stage	Implementation task	Acceptance criterion
1	Audit instrumentation, calibrate sensors, standardize grade recipes	Reliable time-synchronized data and validated laboratory moisture reference
2	Optimize existing PID/cascade loops and safety interlocks	Stable temperature/flow control without oscillation or constraint violation
3	Develop and validate outlet-moisture soft sensor	Prediction error and drift remain within plant-defined quality tolerance
4	Deploy supervisory MPC in advisory mode	Recommendations are stable, feasible and accepted by operators
5	Close supervisory loop with hard constraints and fallback logic	Automatic operation maintains moisture and safety under tested disturbances
6	Add economic optimization and model monitoring	Lower specific energy without deterioration of quality indicators

Expected technical effect and limitations

The expected technical effect of the proposed architecture is a reduction in outlet-moisture variability, fewer off-specification excursions, lower thermal-energy consumption and reduced dependence on manual intervention. These benefits arise from three mechanisms: direct quality feedback through online or estimated moisture, predictive compensation for residence-time delay, and coordinated optimization of thermal duty and gas/solids flow. The literature provides strong support for each individual element: PVC-specific studies quantify the energy sensitivity and multistage-drying potential (1, 2), while general industrial-dryer studies show the advantages of MPC and intelligent control for nonlinear, delayed processes (5–8).

Nevertheless, advanced control cannot compensate for poor mechanical performance. Maldistribution of solids, fouled heat-transfer surfaces, unstable fluidization, leaks or inaccurate feed measurement can invalidate the process model. The system must therefore include model-performance monitoring, sensor validation and an automatic fallback to safe conventional control. AI-based models must also be retrained or recalibrated when resin grade, equipment configuration or operating range changes substantially. For industrial deployment, explainability and operator acceptance are as important as prediction accuracy.

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CONCLUSION

The PVC drying section is a suitable target for intelligent automation because it combines high energy demand with strict moisture and thermal-quality requirements. Literature on PVC powder drying confirms that inlet air conditions, particle-scale transfer and equipment configuration strongly influence performance, while multistage pneumatic and fluidized-bed drying can reduce specific energy use (1, 2). A modern control system should therefore move beyond independent temperature loops toward direct control of product moisture and coordinated optimization of the whole drying train.

The developed concept combines reliable field instrumentation, PLC/DCS regulatory control, online moisture measurement, a soft sensor, MPC, fuzzy supervisory logic and SCADA-based performance monitoring. The recommended hierarchy allows advanced functions to be added without sacrificing deterministic safety control. MPC is proposed for constrained multivariable moisture control; fuzzy logic is used for nonlinear supervisory adaptation; and AI models are used primarily for soft sensing and computational acceleration. The resulting system provides a practical framework for stabilizing product quality, reducing over-drying, minimizing energy consumption and supporting predictive diagnostics. The next stage of research should include plant-specific system identification, validation on historical and pilot data, comparison with the existing control strategy, and controlled industrial trials under several PVC grades and feed-moisture disturbances.

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