HSR (LONDON),
HOUGHTON STREET REVIEW JOURNAL
ISSN: 2058-5519|Impact factor-15.9
http://houghtonstreetreview.com/index.php/hsr

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

Doctoral Researcher: Pariso **Mukhammadrezaevna Sharipova**

Scientific Supervisor: **Sanjar Bakhriddinovich Boybutaev**

Affiliation: Bukhara State Technical University, Uzbekistan

Doi: https://doi.org/10.5281/zenodo.23371511

Abstract: This study develops a structured automation and intelligent control concept for suspension-grade polyvinyl chloride (S-PVC) drying. The proposed architecture combines industrial instrumentation, a model-assisted outlet-moisture soft sensor, online bias adaptation, and constrained model predictive control (MPC). A control-oriented drying model represents moisture removal by an effective rate coefficient and first-order outlet dynamics with transport delay. A reproducible four-hour numerical experiment compares a conventional PI controller with the bias-adaptive MPC under stepwise variations in wet-cake moisture. For the explicitly assumed nominal parameters, MPC reduced the calculated mean utility-demand proxy from 303.19 to 300.31 kW (0.95%) and reduced the proportion of simulated time above the illustrative 0.43% dry-basis moisture limit from 20.4% to 0.0%. A ±10% kinetic-parameter sensitivity test showed both the value and the limitations of online model correction. These are model-based findings, not results of industrial commissioning or laboratory validation. The paper specifies an implementation and validation route for production-scale deployment.

Keywords: polyvinyl chloride; suspension PVC; fluidized-bed drying; industrial automation; soft sensor; predictive control; energy efficiency.

INTRODUCTION

Drying is a decisive finishing operation in the production of suspension polyvinyl chloride (S-PVC). Following suspension polymerization and mechanical dewatering, porous wet-cake particles retain water that must be removed before packaging, storage, or downstream processing. Published studies of industrial PVC lines describe combinations of pneumatic and fluidized-bed dryers and demonstrate that both external convective transfer and internal moisture migration determine the drying response (1, 3, 4). Feed moisture, gas conditions, particle behavior, and residence-time distribution therefore generate a coupled and disturbance-sensitive process.

Improving the drying stage is not equivalent to increasing the inlet-air temperature. Excess heating and airflow raise utility demand, while insufficient removal produces off-specification resin and may complicate handling. In a study of industrial PVC drying, de Araújo et al. evaluated economical moisture and temperature control (2). Investigations of pneumatic pre-drying and two-stage fluidization likewise indicate a significant opportunity for reducing specific energy consumption

HSR (LONDON),
HOUGHTON STREET REVIEW JOURNAL
ISSN: 2058-5519|Impact factor-15.9
http://houghtonstreetreview.com/index.php/hsr

through the appropriate process configuration (5, 6). General drying literature supports simultaneous consideration of heat and mass transfer, equipment hydraulics, energy intensity, and material quality (7, 8).

Conventional independent feedback loops are necessary for reliable operation but can respond slowly to wet-cake variability and do not explicitly coordinate energy demand and moisture constraints. Industrial MPC provides a systematic way to handle interacting manipulated variables and operational limits (9, 10, 13). In addition, inferential or "soft" sensors can estimate properties that are difficult to measure continuously, provided sensor quality, model drift, and calibration are monitored (11, 12). Recent reviews of data-driven drying systems emphasize the potential of hybrid physical and statistical models, while also identifying validation and transferability as persistent challenges (15).

The objective of this work is to formulate an implementable intelligent-control architecture for S-PVC drying and quantitatively compare its nominal behavior with a PI benchmark using a fully disclosed illustrative model. The contribution is a unified process–information–control design, an energy- and quality-aware move-blocking MPC formulation, and a sensitivity analysis with online prediction-bias correction. No unreported experimental data, plant measurements, or trained machine-learning datasets are assumed.

MATERIALS AND METHODS

Process boundary, monitored variables, and instrumentation

The reference configuration comprises a centrifugal wet-cake discharge, an optional pneumatic pre-dryer, and a finishing fluidized-bed dryer. The manipulated variables are inlet-air temperature T (°C) and dimensionless airflow ratio F (relative to nominal flow). The principal quality indicator is discharged resin moisture Xout on a dry basis (kg water/kg dry PVC). The disturbance Xin is incoming cake moisture on the same basis. Conversion to wet basis is Xwb = Xdb/(1 + Xdb); the distinction is necessary when interpreting product specifications and laboratory reports. Thermocouples, airflow and pressure transmitters, humidity sensors, motor-power metering, and a validated outlet-moisture analyzer or laboratory samples provide the plant data infrastructure (1, 4, 7).

HSR (LONDON),
HOUGHTON STREET REVIEW JOURNAL
ISSN: 2058-5519|Impact factor-15.9
http://houghtonstreetreview.com/index.php/hsr

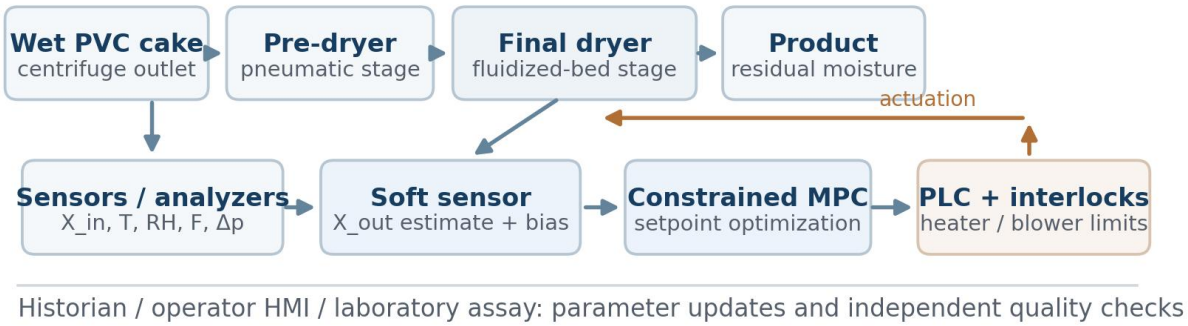


Figure 1. Proposed automation architecture and information flow for S-PVC drying (conceptual design).

The real-time layer is assigned to a programmable logic controller (PLC) and existing safety interlocks; a supervisory computer receives conditioned measurements, estimates residual moisture, and dispatches bounded setpoints. The supervisory algorithm must never bypass independent protections for high temperature, excessive bed pressure drop, airflow loss, or heater faults. Equipment-state diagnosis and sensor redundancy follow established process fault-management principles (14).

Control-oriented moisture and energy model

A reduced-order relationship is used for controller comparison rather than a CFD representation. Its equilibrium-like outlet moisture decreases exponentially with an effective drying-rate coefficient k(T,F), consistent with the qualitative transport trends reported for PVC powder (1, 3). The assumed discrete outlet dynamics include a lag and a transport delay:

$$X^* = X_{eq} + (X_{in} - X_{eq}) \exp[-k(T,F)\,\tau_{res}] \quad (1)$$

$$k(T,F) = 0.0836 \exp[0.028(T - 95)]\, F^{0.55} \quad (\text{min}^{-1}) \quad (2)$$

$$X_{out,k+1} = X_{out,k} + (\Delta t / \tau_d)(X^*_{k-d} - X_{out,k}) \quad (3)$$

Here X_{eq} is the limiting moisture, τ_{res} denotes nominal residence time, τ_d represents an effective outlet response lag, and d is a discrete transport delay. Equation (2) is a deliberately assumed local surrogate, not a kinetic law calibrated for a named PVC grade. A first-principles implementation would additionally require heat balances, gas humidity, product temperature, particulate hydrodynamics, and equipment-specific calibration (3, 4, 7).

Table 1. Defined conditions for the illustrative numerical experiment.

Variable / parameter	Assumed value	Engineering interpretation
Dry-solid throughput	1,000 kg h^{-1}	Illustrative feed basis
Cake moisture Xin	0.25 to 0.35 kg kg^{-1} d.b.	Scheduled feed disturbances

HSR (LONDON),
HOUGHTON STREET REVIEW JOURNAL
ISSN: 2058-5519|Impact factor-15.9
http://houghtonstreetreview.com/index.php/hsr

Variable / parameter	Assumed value	Engineering interpretation
Moisture target / upper limit	0.0040 / 0.0043 kg kg^{-1} d.b.	0.40% / 0.43% dry basis
Equilibrium term Xeq	0.0015 kg kg^{-1} d.b.	Assumed kinetic floor
Residence time τres	55 min	Effective model residence time
Outlet lag τd / delay d	12 min / 4 samples	First-order lag / transport
Sampling interval Δt	1 min	Supervisory calculation period
Allowable T / F	90–108 °C / 0.94–1.12	Supervisory actuator bounds

For comparative accounting, utility power is approximated by the transparent linear proxy $P = 260 + 5.5(T - 90) + 110(F - 0.90)$ kW. It is neither a measured heater duty nor a verified plant energy balance. Specific energy consumption (SEC) is the sum of hourly utility energy divided by the sum of evaporated water, estimated as dry-solid throughput multiplied by (Xin − Xout). The same assumptions and disturbance history are imposed on both controllers.

Soft-sensing, predictive controller, and safety logic

The proposed inferential moisture module combines a physics-based one-step prediction with a slowly adjusted output bias. With an available moisture estimate Xobs, the implied quasi-steady moisture can be recovered from successive observations and the lag model. The resulting innovation updates an exponentially weighted bias b: $b_{k+1} = 0.80b_k + 0.20[X^*_{obs,k} - X^*_{model,k}]$, bounded to ±0.003 kg kg^{-1}. The MPC predictor uses X*model + b. This is an elementary adaptive model correction; it is not a trained neural network. For the numerical test, Xobs is assumed noiseless so that the bias-correction mechanism can be isolated. Before use in production, this observation channel must be replaced or validated by an online moisture instrument, a calibrated soft sensor, and periodic independent assays (11, 12, 15).

At each minute, move-blocking MPC selects candidate constant T and F setpoints over a 30-minute prediction horizon and implements only their first one-minute action. Its objective combines normalized outlet-moisture tracking error, a strong soft penalty above an early-warning threshold of 0.00422 kg kg^{-1}, predicted utility demand, and squared actuator movements. Bound constraints require $|\Delta T| \le 2$ °C min^{-1} and $|\Delta F| \le 0.025$ min^{-1}, in addition to the Table 1 ranges. The objective is minimized using a bounded numerical optimizer, with the previous feasible command retained if optimization or instrumentation fails (9, 10, 13).

$$J = \Sigma_{j=1\ldots30}\,[0.9e_j^2 + 10\,\max(0, g_j)^2 + 0.8q_j^2] + 0.4r_T^2 + 0.4r_F^2 \qquad (4)$$

In Eq. (4), $e_j = (\hat{X}_j - 0.0040)/0.001$, $g_j = (\hat{X}_j - 0.00422)/0.001$, $q_j = (P_j - 260)/70$, $r_T = \Delta T/2$, and $r_F = \Delta F/0.025$. The comparator is a bounded PI loop with fixed F = 1.0: $e_k = (X_{out,k} - 0.0040)/0.001$, $I_{k+1} = \text{clip}(I_k + 0.055e_k, -5.5, 5.5)$, and $T_{cmd} = \text{clip}(95 + 2.4e_k + I_k, 90, 108)$, also subject to the 2 °C min^{-1} rate limit. These tuning constants are illustrative, not plant-approved settings.

HSR (LONDON),
HOUGHTON STREET REVIEW JOURNAL
ISSN: 2058-5519|Impact factor-15.9
http://houghtonstreetreview.com/index.php/hsr

Experimental design and performance indicators

A deterministic 240-minute test uses cake moisture Xin = 0.25 (minutes 0–59), 0.35 (60–134), 0.27 (135–189), and 0.25 kg kg^{-1} d.b. thereafter. Both controllers begin at T = 95 °C and F = 1.0. Performance measures are target MAE, peak moisture, fraction of time above 0.43% d.b., mean utility-power proxy, and SEC. In sensitivity runs, the plant rate coefficient is multiplied by 0.90 or 1.10, while MPC predicts with its nominal coefficient plus adaptive bias. All comparisons are numerical, not industrial validation.

RESULTS

The nominal simulated outlet-moisture histories are shown in Figure 2. The feed step at minute 60 raises the drying load and challenges the controller following the modeled material-transport delay. PI recovers toward the 0.40% d.b. target but reaches a transient peak of 0.4500% d.b. The predictive strategy anticipates part of the incoming load from Xin and maintains a lower peak of 0.4223% d.b. by coordinated setpoint adjustments. The MPC trajectory remains closer to the upper operating band than PI in steady periods because its objective also penalizes energy use; hence its mean absolute target error is slightly higher.

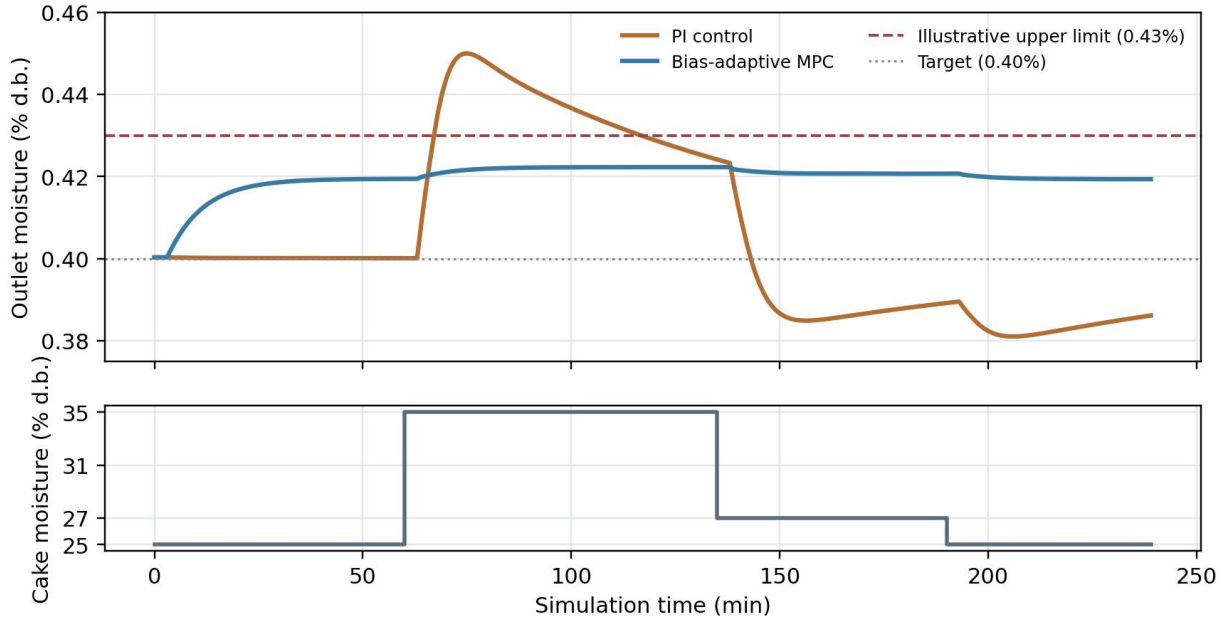


Figure 2. Simulated product-moisture response and specified inlet-cake moisture schedule (nominal model).

Table 2. Comparative performance in the deterministic nominal simulation.

Indicator	PI benchmark	Adaptive MPC
Mean absolute error (% d.b.)	0.0169	0.0196

HSR (LONDON),
HOUGHTON STREET REVIEW JOURNAL
ISSN: 2058-5519|Impact factor-15.9
http://houghtonstreetreview.com/index.php/hsr

Indicator	PI benchmark	Adaptive MPC
Peak outlet moisture (% d.b.)	0.4500	0.4223
Time above 0.43% d.b. limit (%)	20.4	0.0
Mean utility proxy (kW)	303.19	300.31
Specific utility energy (kWh kg^{-1} water)	1.0760	1.0663

On the defined proxy, MPC decreases average utility power by 2.88 kW, equivalent to 0.95% of the PI benchmark. Figure 3 indicates cumulative energy of 1,212.77 kWh for PI and 1,201.24 kWh for MPC over the four-hour horizon. This reduction is modest and strictly model-dependent: the two controls are compared at different moisture-tracking priorities, not at experimentally established equal product-quality operating points.

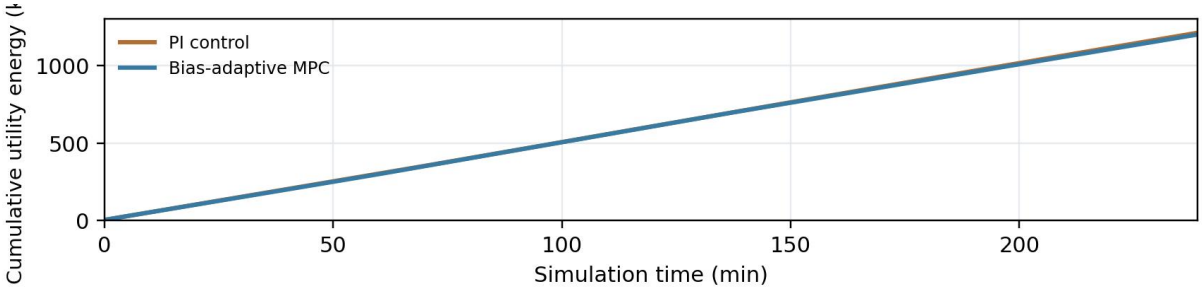


Figure 3. Cumulative simulated energy proxy for the two supervisory-control strategies.

Table 3. Sensitivity to ±10% change in the actual drying-rate coefficient.

True k multiplier	Controller	Peak moisture (% d.b.)	Time above limit (%)	Mean power (kW)
0.90	PI	0.5464	58.3	321.20
0.90	Adaptive MPC	0.5464	12.5	320.69
1.00	PI	0.4500	20.4	303.19
1.00	Adaptive MPC	0.4223	0.0	300.31
1.10	PI	0.4185	0.0	287.53
1.10	Adaptive MPC	0.4129	0.0	283.67

The sensitivity experiment exposes a material limitation. When the actual kinetic coefficient is 10% below its nominal value, both controllers initially face a wetter product, and even adaptive MPC exceeds the moisture limit for 12.5% of the run. A positive 10% coefficient shift gives compliant operation under both strategies. Accordingly, bias adaptation improves the tested response but does not guarantee constraint satisfaction under equipment or product-grade changes.

HSR (LONDON),
HOUGHTON STREET REVIEW JOURNAL
ISSN: 2058-5519|Impact factor-15.9
http://houghtonstreetreview.com/index.php/hsr

DISCUSSION

The results support using inlet-moisture information in supervisory drying control, rather than relying entirely on feedback from final-product moisture. Such feedforward is physically reasonable because PVC drying depends on the interactions of initial moisture, airflow, temperature, and intra-particle transport (1, 3, 5). The quality-energy compromise must be interpreted carefully: MPC reduced peak moisture and the duration of simulated off-limit operation, but its tracking MAE was higher under nominal conditions. This reflects the actual objective-weight selection rather than an unconditional superiority of one controller.

The simulated nominal 0.95% utility reduction must not be generalized to a plant without validating the heat-demand proxy and production throughput. Published PVC industrial studies have reported larger improvements from process and control restructuring, but those findings concern specific equipment and operating envelopes and cannot be used as validation of the present numbers (2, 5, 6). The proposed simplified model also omits grade-dependent particle-size distributions, bed mixing, product-temperature nonuniformity, possible fouling, and inlet-gas humidity fluctuations. Accurate plant identification or a higher-fidelity digital twin is required before quantitative claims can be made (4, 7, 8).

Deployment requires calibrated sensors, independent moisture assays, and external soft-sensor validation. Testing must cover feed disturbances, actuator limits, model drift, optimizer failure, and safe fallback to PLC/PID. Independent safety interlocks are mandatory (11, 12, 14, 15). Plant trials should report grade-wise error and measured energy intensity.

CONCLUSIONS

An integrated automation concept for S-PVC drying has been developed by combining on-line process measurements, a model-based moisture estimate with adaptive bias compensation, safety-constrained actuation, and a move-blocking MPC supervisor. Under the explicitly defined nominal model and four-hour disturbance schedule, MPC reduced the maximum simulated outlet moisture from 0.4500% to 0.4223% d.b., eliminated sampled exceedances of an illustrative 0.43% d.b. threshold, and lowered modeled average utility demand by 0.95%. The sensitivity study also identified residual noncompliance under slower-than-nominal kinetics. These outcomes substantiate a design and testing hypothesis only; laboratory calibration and prospective industrial validation are needed before deployment or claims of achieved manufacturing savings.

References

1. Aubin, A., Ansart, R., Hemati, M., Lasuye, T., & Branly, M. (2014). Modeling and simulation of drying operations in PVC powder production line: Experimental and theoretical study of drying kinetics on particle scale. Powder Technology, 255, 120–133. https://doi.org/10.1016/j.powtec.2013.08.019
2. de Araújo, A. C. B., Vasconcelos, L. G. S., Alves, J. J. N., & Shang, H. (2011). Optimal operation of an industrial PVC dryer. Drying Technology, 29(1), 19–34. https://doi.org/10.1080/07373937.2010.482713

HSR (LONDON),
HOUGHTON STREET REVIEW JOURNAL
ISSN: 2058-5519|Impact factor-15.9
http://houghtonstreetreview.com/index.php/hsr

3. Aubin, A., Ansart, R., Hemati, M., Lasuye, T., & Branly, M. (2016). Determination of PVC powder drying kinetics at particle scale: Experimental study and modeling. Drying Technology, 34(16), 2000–2023. https://doi.org/10.1080/07373937.2016.1155596
4. Tacidelli, A. R., Pereira Neto, A. T., Brito, R. P., de Araújo, A. C. B., Vasconcelos, L. G. S., & Alves, J. J. N. (2012). Modeling and simulation of industrial PVC drying in fluidized beds with internal heat source. Chemical Engineering & Technology, 35(12), 2107–2119. https://doi.org/10.1002/ceat.201100713
5. Banooni, S., Hajidavalloo, E., & Dorfeshan, M. (2018). Experimental and numerical study of the effects of pre-drying of S-PVC using a pneumatic dryer. Powder Technology, 338, 220–232. https://doi.org/10.1016/j.powtec.2018.06.027
6. Dorfeshan, M., Mehrzad, S., & Hajidavalloo, E. (2022). Experimental and numerical investigation of specific energy consumption of the two-stage pneumatic-fluidized bed drying of suspension-grade polyvinyl chloride. Drying Technology, 40(2), 371–386. https://doi.org/10.1080/07373937.2020.1812632
7. Mujumdar, A. S. (Ed.). (2014). Handbook of industrial drying (4th ed.). CRC Press.
8. Kudra, T., & Mujumdar, A. S. (2009). Advanced drying technologies (2nd ed.). CRC Press.
9. Qin, S. J., & Badgwell, T. A. (2003). A survey of industrial model predictive control technology. Control Engineering Practice, 11(7), 733–764. https://doi.org/10.1016/S0967-0661(02)00186-7
10. Morari, M., & Lee, J. H. (1999). Model predictive control: Past, present and future. Computers & Chemical Engineering, 23(4–5), 667–682. https://doi.org/10.1016/S0098-1354(98)00301-9
11. Kadlec, P., Gabrys, B., & Strandt, S. (2009). Data-driven soft sensors in the process industry. Computers & Chemical Engineering, 33(4), 795–814. https://doi.org/10.1016/j.compchemeng.2008.12.012
12. Kano, M., & Fujiwara, K. (2013). Virtual sensing technology in process industries: Trends and challenges revealed by recent industrial applications. Journal of Chemical Engineering of Japan, 46(1), 1–17. https://doi.org/10.1252/jcej.12we167
13. Seborg, D. E., Edgar, T. F., Mellichamp, D. A., & Doyle, F. J., III. (2016). Process dynamics and control (4th ed.). Wiley.
14. Isermann, R. (2006). Fault-diagnosis systems: An introduction from fault detection to fault tolerance. Springer. https://doi.org/10.1007/3-540-30368-5
15. Talele, P., Chaudhari, V. D., Talele, H., & Chaudhari, D. V. (2025). Evolution of drying process modeling: From mathematical foundations to machine learning-driven prediction and control. Journal of Food Process Engineering, 48(12), e70300. https://doi.org/10.1111/jfpe.70300