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Optimising energy usage of a semi-continuous fluidised bed dryer using digital twin technology and energy management strategies

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ABSTRACT

Pharmaceutical manufacturers are under increasing pressure to reduce energy consumption and enhance sustainability to meet net-zero emission targets. Achieving these goals requires advanced methodologies capable of capturing complex process dynamics and driving realtime optimisation. Industry 4.0 technologies – particularly Digital Twins (DTs) – offer significant potential, yet their effectiveness can be limited by undetected process anomalies and subtle energy-performance deviations. This study presents a novel DT integrated framework that combines energy management techniques, statistical monitoring, and a newly defined Energy Performance Indicator (EnPI) to optimise a semicontinuous fluidised bed dryer (FBD) within the GEA Consigma25 line at the Diamond Pilot Plant, University of Sheffield. Realtime experimental data and DT outputs were analysed using CUSUM (Cumulative Sum) deviation analysis, enabling sensitive detection of energy-moisture performance shifts that the DT alone could not identify. Results highlight 60°C as the optimal drying air temperature, delivering superior energy efficiency across liquid-to-solid ratios of 0.18 and 0.30, with opportunities for further refinement within the 50–60°C range. By bridging gaps in realtime multi-objective monitoring, this integrated approach provides actionable insights for energy-efficient, quality-driven process control and establishes a scalable pathway towards sustainable pharmaceutical manufacturing.

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Continuous manufacturing; sustainable energy management; fluidised bed dryer; diamond pilot plant; digital twin; cumulative sum analysis

Introduction

Sustainable manufacturing aims to produce high-quality products while minimising energy and material consumption, thus mitigating the environmental impact of the industry (Machado, Winroth, and Ribeiro da Silva 2019; Mascia et al. 2013). Escalating energy costs, stringent regulations, and resource scarcity have intensified this focus, particularly within the pharmaceutical industry, which is experiencing increased global demand and shifting towards personalised medicine (Dukart et al. 2022; Erol et al. 2020; Herrmann et al. 2014; UK government 2010). Digital Twin (DT) technology, which enables advanced integration of data analysis and process control, has become pivotal in enhancing manufacturing safety, quality, and consistency (Chen et al. 2020; Khanal and Lenhoff 2021; Lee et al. 2015). Nevertheless, the transformative potential of DT technologies in continuous manufacturing remains largely unrealised, necessitating further research and large-scale demonstration, particularly in the pharmaceutical industry, to fully their leverage capabilities (Byrn et al. 2015; Fuller et al. 2020; Ntamo et al. 2025).

Fluidised bed dryers (FBDs), which are critical for drying granulated solids in continuous pharmaceutical manufacturing, are inherently energy-intensive, with reported efficiencies often as low as 55–60%, highlighting substantial opportunities for optimisation (Majumder et al. 2022). To address these inefficiencies, this study employs DT technologies within the Diamond Pilot Plant's (DiPP) GEA Consigma-25 manufacturing line (Ntamo et al. 2022). Effective energy management in this context also requires advanced visualisation tools capable of predictive analytics and providing intuitive, interactive operator interfaces; however, existing solutions frequently lack sufficient usability and functional integration (Gómez-Carmona et al. 2024).

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In response, this work introduces a novel integration of the Cumulative Sum (CUSUM) method – highly sensitive to small, persistent process shifts – with the DT developed for the FBD at DiPP. This combined approach enhances energy efficiency, process stability, proactive maintenance, and data-driven decision-making.

The paper is structured as follows: a review of relevant literature; detailed methodology; global sensitivity and exploratory data analyses; energy management evaluation using the CUSUM approach; and concluding remarks with identified directions for future research.

Literature review

Precise control of semi-continuous pharmaceutical units, such as segmented FBDs, is a growing focus in continuous manufacturing research. Advances in Process Analytical Technology (PAT), including near-infrared (NIR) and Raman spectroscopy coupled with chemometrics, have significantly improved real-time monitoring of moisture content and process dynamics (Fonteyne et al. 2014; Silva et al. 2017). Despite these developments, current drying control strategies remain limited; static or compartment-focused approaches fail to address the interconnected nature of continuous operations, resulting in inadequate disturbance handling, suboptimal product quality and ultimately increased energy consumption (Chablani et al. 2011; De Leersnyder et al. 2023; Ryckaert et al. 2021; Stauffer et al. 2019). Consequently, the inherent complexity of modern pharmaceutical continuous manufacturing control systems, combined with the vast volumes of process data required for real-time multi-objective optimisation, necessitates an integrated, multi-methodological approach that utilise diverse tools and technologies to enable effective real-time optimisation and data-driven decision-making.

DTs provide a powerful solution by creating virtual replicas of physical systems that enable continuous monitoring, predictive modelling, and optimisation of both process performance and energy consumption. This holistic digital framework links operational parameters to their energy footprint, supporting sustainable manufacturing. However, effectively interpreting the vast data generated by DTs requires sensitive statistical tools. CUSUM analysis, known for detecting small, persistent process shifts, addresses this need by providing early warnings of deviations that may impact quality or energy efficiency (Faisal et al. 2018; Vranić and Uzunović 2008). The integration of CUSUM within digital twins thus offers a synergistic approach: DTs supply comprehensive, real-time data, while CUSUM enables rapid detection and diagnosis of anomalies.

Existing studies, however, typically explore DTs, energy optimisation, and statistical process control in isolation, with limited work on their real-time integration for complex systems like FBDs. This research addresses this gap by embedding CUSUM analysis within a predictive DT framework for a FBD in continuous pharmaceutical manufacturing. The proposed methodology enhances energy efficiency, process stability, and proactive control by enabling early intervention before significant deviations occur. By bridging these domains, this work advances real-time monitoring and optimisation strategies and demonstrates their applicability to industrially relevant continuous processes.

Methodology and experimental framework

Experimental facility and equipment

The DiPP at the Faculty of Engineering of the University of Sheffield houses large-scale process units to support research across multiple process industries, with a particular focus on pharmaceuticals (Ntamo et al. 2022). This facility includes a continuous crystallisation unit, filter dryer, and industrial-scale GEA Consigma 25 powder-to-tablet line. Figure 1 illustrates the unit operations of the Consigma 25 line, which is a continuous wet granulation production line that operates at a nominal throughput of 25 kg/h. The process starts with the pre-blended powder being fed into a twin-screw granulator (TSG) with a binder, creating wet granules. These are dried in a segmented fluidised bed dryer and then pneumatically conveyed to a conditioning unit where NIR technology monitors the moisture content and rejects out-of-spec products. The dried granules were milled, blended with additional materials, and compressed into tablets by using a rotary tablet press.

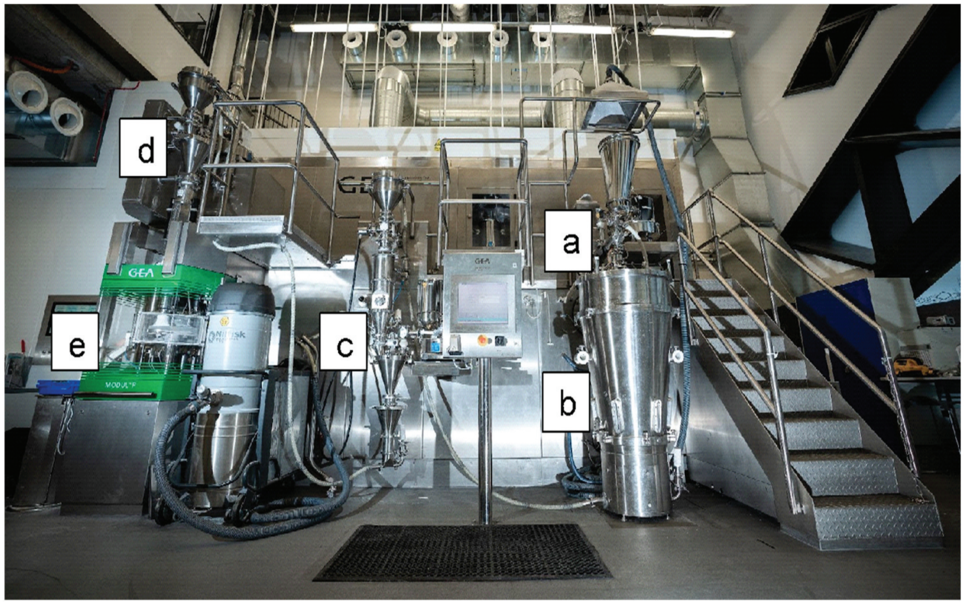

Figure 1. The Consigma 25 line at Diamond Pilot Plant (DiPP): (a) twin screw wet granulator, (b) segmented fluid bed dryer, (c) cone mill, (d) blender and (e) tablet press.

The Consigma-25 line is equipped with an advanced control and monitoring architecture, supported by a dedicated industrial control room housing its state-of-the-art process automation and advanced DT. This infrastructure positions the DiPP as a leading Industry 4.0 research facility (Ntamo et al. 2022). The primary objective of this system is to establish a data-driven, fully automated framework for testing and validating emerging smart manufacturing technologies under realistic conditions.

Figure 2 presents an image of the DiPP's FBD, positioned downstream of the twin-screw granulator within the continuous manufacturing line. The dryer comprises six segmented drying chambers, where wet granules produced in the granulator are fluidised to reduce their moisture content. The resulting dried pharmaceutical granules are subsequently conveyed for further processing into tablets (Fonteyne et al. 2014; Jiang et al. 2022). This FBD serves as the primary unit of investigation in the present study.

In the FBD, wet granules experience fluidisation when hot air is channelled through a perforated bed. Wet granules are suspended in hot air in each cell during drying process (Jiang et al. 2022; Pusapati and Rao

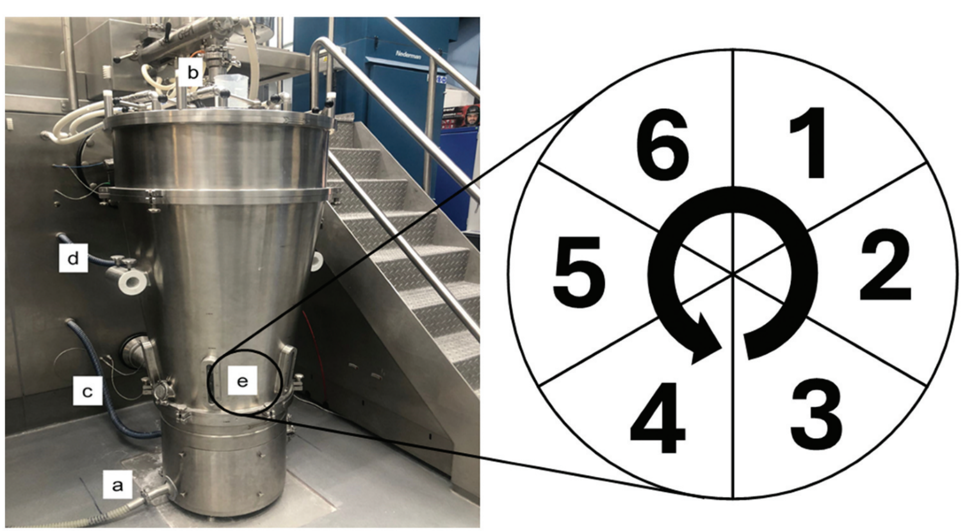

Figure 2. DiPP fluidised bed dryer a) dried granule outlet b) wet granule inlet c) drying air inlet tube d) drying air outlet tube e) six segmented drying cells.

2014). This causes the moisture of the granules to vaporise, with the resulting vapour entrained by the hot air (GD Modules; Jiang et al. 2022). The temperature and flow rate of the hot air are critical elements for lowering the energy consumption in the FBD. Using these factors can minimise the drying time and hot-gas temperatures, resulting in energy savings while maintaining the product at the desired moisture content (Jiang et al. 2022).

FBD digital model

A mechanistic digital model of the fluidised bed dryer (FBD) was developed using Siemens gPROMS Formulated Products (v2023.2.0.55304) to perform global sensitivity analysis and identify parameters influencing energy consumption. gPROMS provides an integrated platform for digital design and optimisation of pharmaceutical manufacturing processes, with modelling templates for key operations such as drying, milling, and tableting (Fonteyne et al. 2014; gPROMS FormulatedProducts). The model leverages global system and sensitivity analyses to evaluate process dynamics and guide optimisation and safety assessments.

Key dynamic variables simulated include product temperature, moisture content, and inlet air relative humidity – critical indicators of energy efficiency and product quality (Aghbashlo et al. 2014; Chablani et al. 2011; De Leersnyder et al. 2018; Khoshtaghaza, Darvishi, and Minaei 2014; Silva et al. 2017; Yusuf et al. 2019). The modelling framework is based on Burgschweiger and Tsotsas (Burgschweiger and Tsotsas 2002) and assumes instantaneous particle elutriation, perfect mixing, accumulation of solids and vapour, and falling-rate drying kinetics. Particle porosity is assumed to increase during drying, with no shrinkage occurring. For the segmented dryer configuration, only one segment is assumed to load or discharge at a time. Consequently, differences between conventional and segmented models arise solely from the governing equations specific to each configuration (Figure 3) (Ryckaert et al. 2021).

While several methods are available to estimate mass and heat transfer coefficients, this study employs the Burgschweiger and Tsotsas correlations (Burgschweiger and Tsotsas 2002), which are appropriate for externally controlled drying regimes. The heat transfer between the fluidising gas and particles is defined as:

$$\dot{q}_{s,e,k} = \alpha_{s,g}\frac{\pi}{6}\int_{0}^{\infty} x^2 f_b(x)\left(T_p - T_g\right) \tag{1}$$

where $\alpha_{s,g}$ is the heat transfer coefficient between the solid and gas phase, $f_b(x)$ is the size distribution in the drying cell whilst T_p and T_g are the particle and gas temperature, respectively.

The mass transfer coefficient $k_{c,i}$ is calculated from the bulk Sherwood number as below:

$$Sh_{bulk,i} = \frac{k_{c,i}d_p}{D_i} i \in C_{LV} \tag{2}$$

where $Sh_{bulk,i}$ is the bulk Sherwood number; d_p and D_i are the particle diameter and diffusion coefficient of species i.

The bulk Sherwood number $Sh_{bulk,i}$ is given by.

$$Sh_{bulk,i} = \frac{\in R_e S_c}{A_V L}\ln\left(1 + \frac{A_V L S_h}{R_e S_c}\right) \tag{3}$$

where ε and R_e are the bulk Sherwood number correction and Reynolds number; S_h and S_c are the Schmidt number and single particle Sherwood number, respectively. A_V and L are the particle surface area per volume fraction and bed height in the fluid bed dryer.

And the single particle Sherwood number Sh is expressed as a function of Reynolds number $Re_0^{1/2}$ and Schmidt number $Sc_i^{1/3}$ and gives.

$$Sh = 2 + 0.6Re_0^{1/2} * Sc_i^{1/3} \tag{4}$$

The Schmidt number Sc_i is given as

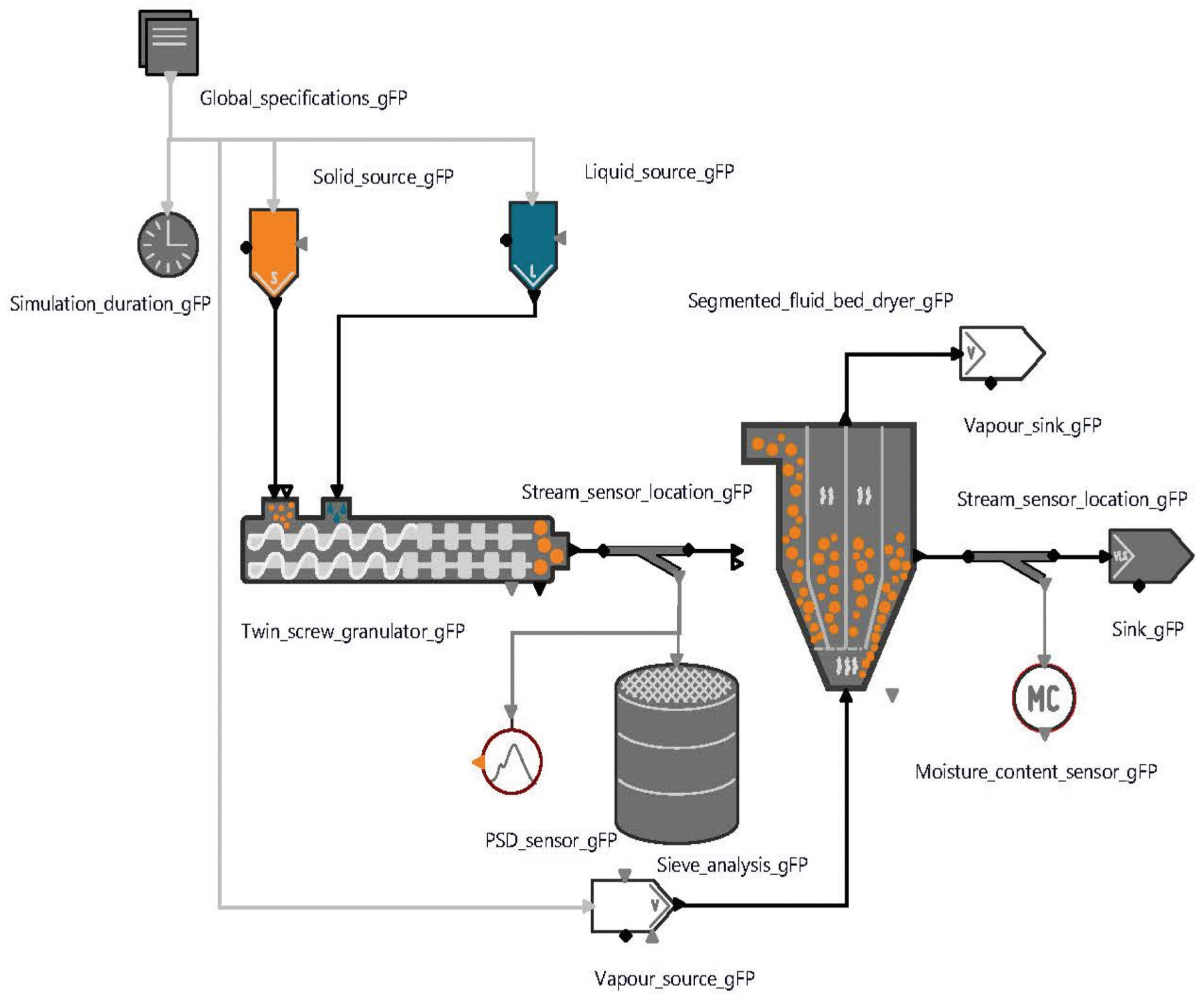

Figure 3. Integrated flowsheet of the of the twin screw granulator and six-segmented fluidised bed dryer in gPROMS Formulated products (v2023.2.0.55304).

$$Sc_i = \frac{\mu_g}{\rho_g D_i} i \in C_{LV} \quad 5$$

where μ_g is the viscosity of the gas phase.

The Reynolds number is given as:

$$Re_o = \frac{d_p \mu_0 \rho_g}{\mu_g} \quad 6$$

where μ_0 denotes the superficial velocity of gas.

Experimental setup and data acquisition

Experimental campaigns were designed to optimise the energy efficiency of the fluidised bed dryer (FBD) while maintaining unit performance. Experiments were conducted at drying air temperatures of 40°C, 50°C, 60°C, and 70°C, and at two liquidtosolid (L/S) ratios: 0.18 and 0.30. The feed formulation consisted of 72% lactose (DFE Pharma, Germany), 24% microcrystalline cellulose, and 4% PVP (Harke Pharma GmbH, Germany), granulated with distilled water in the twin screw granulator (TSG) to increase moisture content. The resulting wet granules were transferred to the segmented FBD, where each of the six drying chambers required approximately 660 s to complete a cycle.

Table 1. Summary of operating conditions applied during the experimental campaigns for the Consigma 25.

Process Parameter	Value
Twin screw granulator (TSG)	
Powder feed flow rate	5 kg.h^{-1}
L/S Ratio	0.18 and 0.3
Screw speed	500 rpm
Fluidised bed dryer (FBD)	
Inlet air flow rate	360 m^3.h^{-1}
Cell filling time	240s
Cell drying time	660s

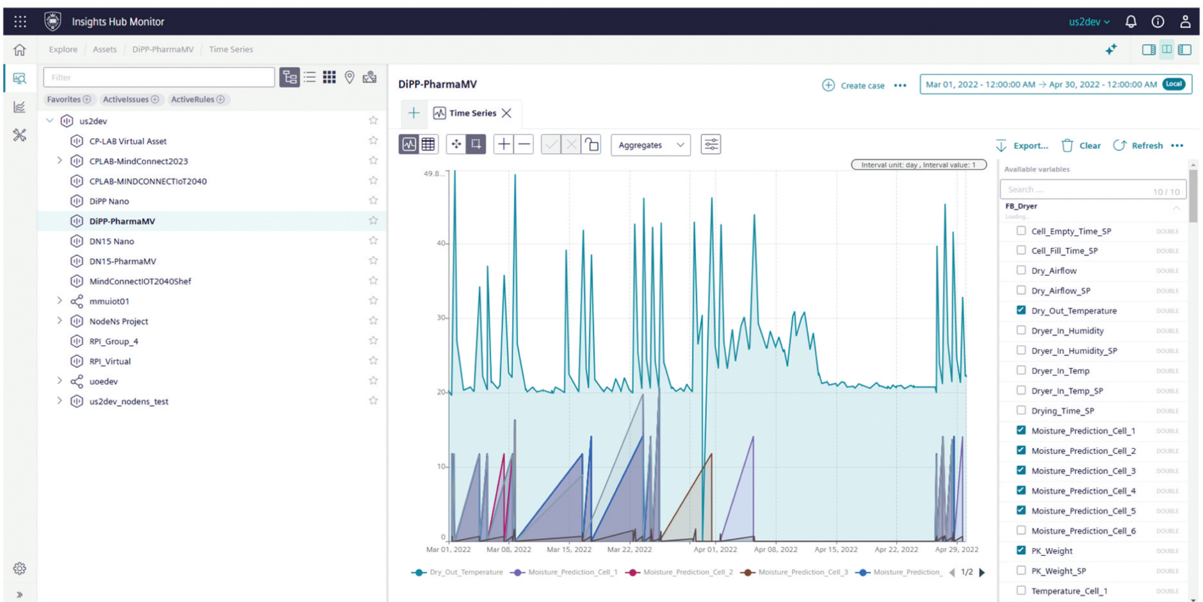

Figure 4. Real-time temperature and moisture content readings from DiPP's DT Siemens Insight Hub.

Product temperature was continuously recorded via integrated probes located at the base of each chamber, while final moisture content was measured inline using a calibrated near-infrared (NIR) probe (FP710e, NDC Technology, UK) positioned after the dryer and prior to milling. The NIR probe was calibrated against loss-on-drying (LOD) measurements (M35, Sartorius GA, Germany) to ensure accuracy. Following initial runs at an L/S ratio of 0.18, the ratio was increased to 0.30 and experiments repeated. This procedure was performed across all four drying air temperatures, providing 6 h of experimental data for performance evaluation. Standard operational parameters are summarised in Table 1.

Data management and processing

Process data from the Consigma25 line were automatically captured by the DiPP DT, which aggregates measurements into a centralised repository and transmits them to the Siemens Insight Hub (Figure 4) for storage and analysis. Data were logged every 5 s to balance resolution and file size, supplemented by manual measurements to validate online product temperature and moisture readings. Postprocessing was conducted in Microsoft Excel (Microsoft 365, Version 2411), involving the removal of irrelevant parameters, alignment of key variables (product temperature, moisture content, and inlet/outlet air temperatures), and preparation of cleaned datasets for subsequent energy-performance calculations and analysis.

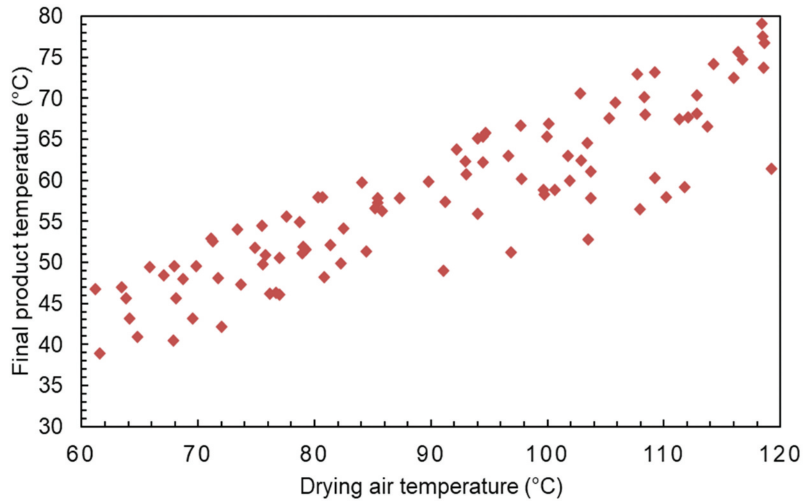

Figure 5. Scatter graph showing drying air temperature (heater outlet temperature) against final temperature of the product. The pattern of data points on the scatter graph reveals the positive correlation between the two variables.

Table 2. Factor sensitivity table for fluidised bed dryer.

Factor	First order effects on product moisture content	Total effects on product moisture content	First orders on temperature of the product	Total effects on temperature of the product
Drying air Temperature (°C)	0.405	0.663	0.793	0.754
Initial granule moisture content ($kg.kg^{-1}$)	0.039	0.040	−0.026	0.000038
Mass flow rate of vapour ($kg.h^{-1}$)	0.592	0.518	0.295	0.220
Temperature setpoint (°C)	0.156	0.000	−0.025	0.000

Global sensitivity analysis

The global sensitivity analysis in this study was performed by varying each process parameter within ±20% of its nominal operational values (Table 1). Variance-based sensitivity indices were calculated using Saltelli's method (Saltelli et al. 2010) to quantify the contribution of individual parameters to the variance in model responses, with computations performed via Monte Carlo simulations. Given the high computational cost of this approach, a quasirandom sampling strategy was employed to efficiently explore the operational space, generating 50–2,000 samples.

Figure 5 and Table 2 summarise the sensitivity analysis outcomes for the FBD experiments in this study. The analysis reveals that drying air temperature is the dominant factor influencing both product moisture content and product temperature, exhibiting strong total effects (0.663 and 0.754, respectively) and notable interaction effects relative to first-order indices (0.405). Vapour mass flow rate also demonstrates a significant positive influence on moisture content (total effect: 0.518) and a moderate effect on product temperature (total effect: 0.220). These results highlight key drivers of dryer performance and underline complex parameter interdependencies, particularly for moisture content, that warrant further investigation for process optimisation.

The findings confirm that drying air temperature is the primary operational variable affecting both critical quality attributes. Figure 5 illustrates this positive correlation: as heater outlet temperature increases, the final product temperature rises accordingly and approaches the inlet drying air temperature with longer residence times. This understanding provides a basis for targeted control strategies to improve energy efficiency and maintain consistent product quality.

FBD experimental results

Temperature profiles from the FBD (Figure 6) exhibited the expected pattern of an initial high temperature, rapid decline during the gradual addition of wet granules, and then gradual recovery in the falling-rate

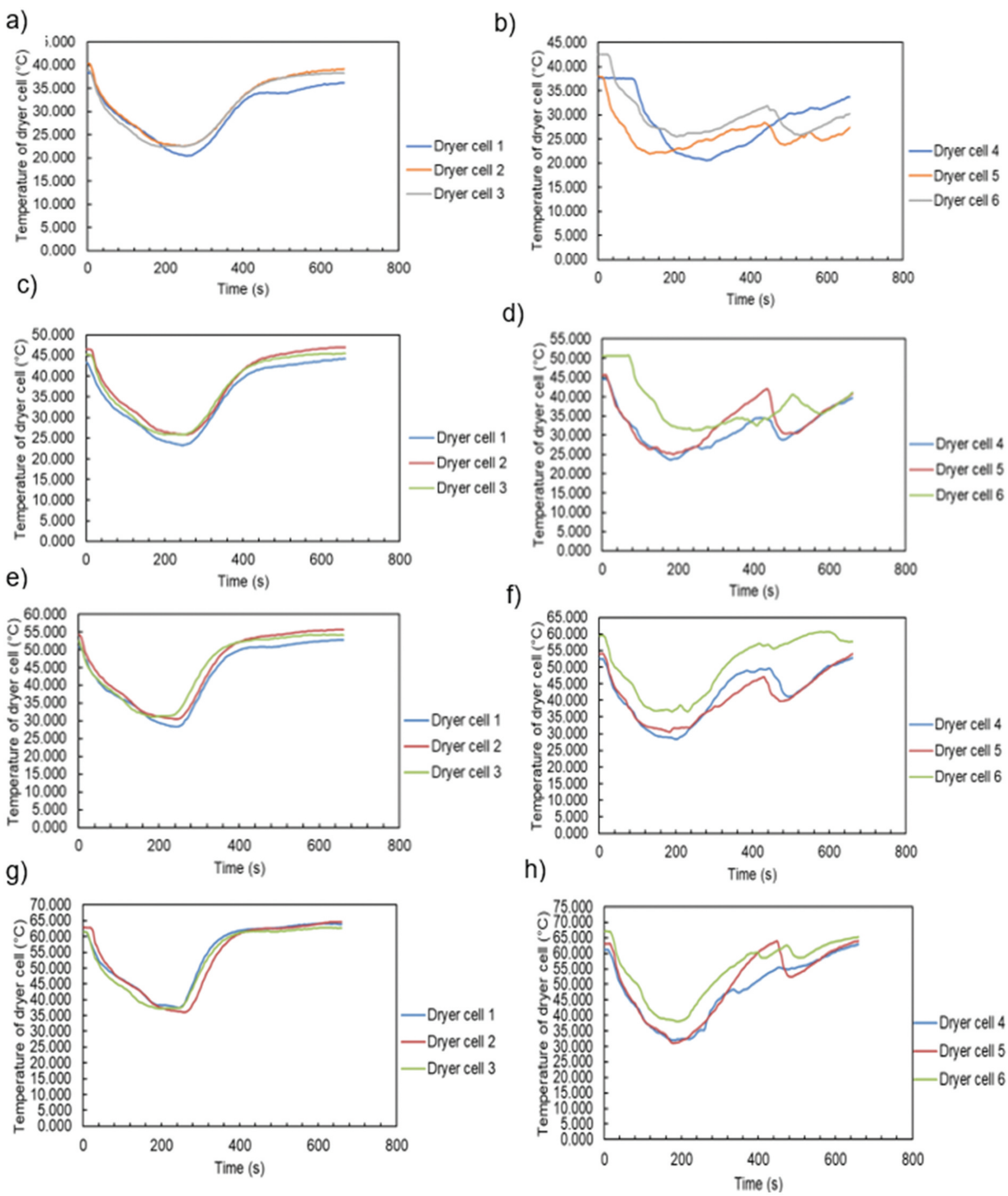

Figure 6. Product temperature profiles of individual dryer cells over time at drying air temperatures of (a) 40°C, (b) 50°C, (c) 60°C, and (d) 70°C for an L/S ratio of 0.18, and (e) 40°C, (f) 50°C, (g) 60°C, and (h) 70°C for an L/S ratio of 0.30.

phase. Minimum temperatures occurred around 260 s, coinciding with moisture evaporation from granules initially at ~ 22°C.

Cells 1–3 showed consistent behaviour at an L/S ratio of 0.18, with final product temperatures of 36–39°C. Increasing the L/S ratio to 0.30 introduced greater variability and reduced final temperatures, reflecting more complex drying dynamics such as wall deposition and particle aggregation. Cells 4–6 displayed more pronounced fluctuations and lower final temperatures, likely due to nonuniform air distribution across the dryer. ANOVA confirmed significant intercell variability ($p < 0.05$) under high-moisture conditions.

Table 3. Moisture content (wet basis) of granules at the inlet and outlet of the fluidised bed dryer across drying air temperatures of 40–70°C for two L/S ratios (0.18 and 0.30).

		L/S = 0.18		L/S = 0.3	
Run	Drying Temperature (°C)	Initial moisture content (%)	Final moisture content (%)	Initial moisture content (%)	Final moisture content (%)
1	40	15.259	6.34	23.084	5.43
2		15.259	5.39	23.084	5.46
3		15.259	5.16	23.084	5.52
4	50	15.259	4.95	23.084	4.9
5		15.259	4.85	23.084	4.9
6		15.259	4.86	23.084	4.87
7	60	15.259	4.76	23.084	4.7
8		15.259	4.66	23.084	4.72
9		15.259	4.7	23.084	4.66

Manual moisture measurements (Table 3) corroborated temperature trends: moisture content decreased with higher drying air temperatures, from 5.63% at 40°C to 4.56% at 70°C (L/S = 0.18). Higher L/S ratios slightly elevated moisture at lower temperatures but had minimal impact at higher temperatures. These findings highlight key operational factors – air temperature and L/S ratio – as dominant drivers of drying uniformity, product quality, and energy efficiency, informing parameter selection for subsequent CUSUM analysis.

FBD energy performance

The energy performance of the FBD was evaluated using a steady-state energy balance framework, treating the dryer as a continuous system. Under steady-state conditions and assuming good insulation, energy accumulation is negligible, and heat losses are minimal. Consequently, the energy entering the system equals the energy leaving the system.

The primary energy inputs are the enthalpy of the inlet drying air and the enthalpy of the wet solids entering the dryer. Energy outputs comprise the enthalpy of the humid exhaust air and the enthalpy of the dried solids. A major portion of the input energy is consumed as the latent heat of vaporisation of water removed from the solids. The general energy balance for the FBD is expressed as:

$$\dot{m}_{air,in}H_{air,in} + \dot{m}_{solid,wet,in}H_{solid,wet,in} = \dot{m}_{air,out}H_{air,out} + \dot{m}_{solid,dry}H_{solid,dry,out} + Q_{loss} \quad (7)$$

where the enthalpy of the air and solids incorporates both sensible and latent heat components, calculated relative to a defined reference temperature. The key terms include:

- **Air enthalpy**:

$$H_{air,in} = C_{p.dryair}\left(T_{air} - T_{ref}\right) + H_{abs}\gamma_0 \quad (8)$$

- **Solid enthalpy**:

$$H_{solid,wet} = C_{p.drysolid}\left(T_{solid,in} - T_{ref}\right) + X_{in}C_{p.water}\left(T_{solid,in} - T_{ref}\right) \quad (9)$$

Here, X is the moisture content of the solid, and λ is the latent heat of vaporisation of water at the drying temperature. For well-insulated systems where $Q_{loss} \approx 0$, the energy balance simplifies to the net heat supplied by the air, which is used to heat the solids and evaporate moisture:

$$Q = \dot{m}_{solid,dry}C_{p.drysolid}\left(T_{solid,out} - T_{solid,in}\right) + \lambda\dot{m}_{solid,dry}\left(X_{in} - X_{out}\right) \quad (10)$$

The equation above was applied to calculate the specific energy consumption of the FBD at two liquid-to-solid (L/S) ratios (0.18 and 0.30). Thermophysical properties of the granule formulation (Cp) and water (λ) were sourced from NIST 2024 data (National Institute of Standards and Technology). The resulting energy consumption values are summarised in Table 4.

Figures 7 and 8 present the relationship between drying air temperature, energy consumption, and final product moisture content for the FBD at L/S ratios of 0.18 and 0.30, respectively. Across both conditions,

Table 4. Calculated energy consumption of the FBD at drying air temperatures of 40–70°C for two liquid-to-solid (L/S) ratios (0.18 and 0.30).

Run	Temperature (°C)	L/S = 0.18 FBD energy consumption (kWh)	L/S = 0.30 FBD energy consumption (kWh)
1	40	525.91	866.71
2		579.94	850.24
3		589.21	854.20
4	50	607.64	898.10
5		618.89	900.73
6		615.40	902.88
7	60	631.48	930.33
8		643.11	931.77
9		637.41	943.66
10	70	663.98	948.94
11		662.62	953.41
12		655.78	956.98

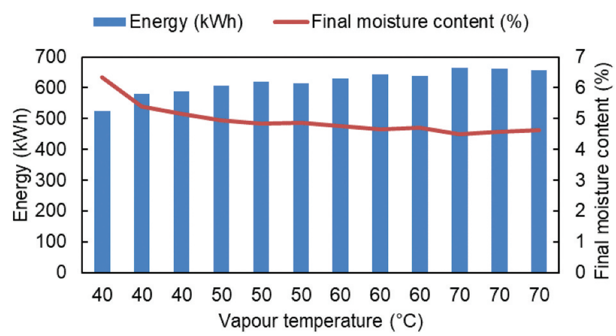

Figure 7. Energy consumption and corresponding final product moisture content of the DiPP FBD at varying drying air temperatures for an initial L/S ratio of 0.18.

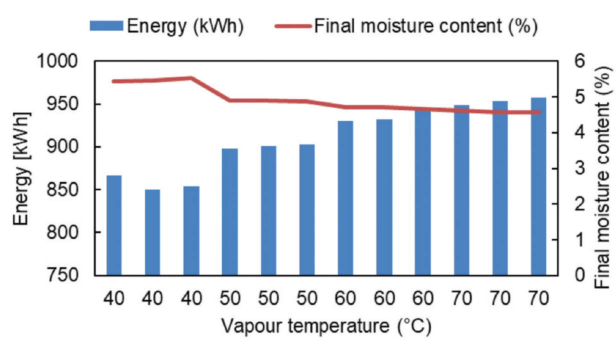

Figure 8. Energy consumption and corresponding final product moisture content of the DiPP FBDat varying drying air temperatures for an initial L/S ratio of 0.30.

increasing drying air temperature resulted in higher energy consumption and lower final moisture content, demonstrating the tradeoff between energy use and moisture removal.

At L/S = 0.18 (Figure 7), energy consumption rose from ~520 kWh at 40°C to over 650 kWh at 70°C, while moisture content decreased from ~6.5% to ~4.3%. At L/S = 0.30 (Figure 8), absolute energy demands were substantially higher, increasing from ~865 kWh at 40°C to ~950 kWh at 70°C, with moisture content following a similar downward trend (5.5% to 4.4%). These results highlight that higher L/S ratios impose greater energy requirements while offering only marginal moisture-reduction benefits at elevated temperatures.

Further ANOVA analysis confirmed the statistical significance of vapour temperature effects on energy consumption. At L/S = 0.18, temperature accounted for ~72% of the variance ($p = 0.014$), while at L/S = 0.30, the effect was markedly stronger, explaining ~99% of the variance ($p < 0.001$). This near-linear

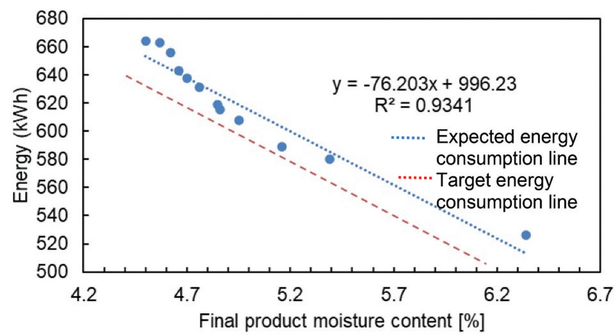

Figure 9. Relationship between energy consumption and final product moisture content for the DiPP fluidised bed dryer at a starting liquid-to-solid (L/S) ratio of 0.18.

relationship underscores vapour temperature as the dominant driver of energy consumption, particularly under higher moisture loading.

Post-hoc pairwise comparisons further revealed that the most pronounced changes in both energy use and moisture content occur between 40°C and higher temperatures. Beyond 50–60°C, incremental increases in temperature continued to raise energy consumption without producing statistically significant reductions in final moisture content. This plateau effect suggests an optimal operational window: temperatures above 50–60°C may incur disproportionate energy penalties relative to moisture-removal gains.

Collectively, these findings demonstrate a clear tradeoff: higher drying air temperatures enhance drying efficiency and reduce final moisture content but at the cost of substantially increased energy consumption. Identifying this balance is essential for optimising process economics and sustainability in continuous pharmaceutical manufacturing.

Energy Performance Indicator (EnPI)

Building on the insights from the earlier global sensitivity analysis and energy-trend evaluations, an Energy Performance Indicator (EnPI) has been introduced as the relationship between energy consumption and final product moisture content:

$$\text{EnPI for FBD} = \text{Energy Consumption}/\text{Final Product Moisture}$$

This metric captures how efficiently energy is utilised to achieve drying objectives and provides a quantitative benchmark for process optimisation. Deviations from the expected EnPI trend may indicate process anomalies, including equipment wear, maintenance interventions, or operator-driven changes.

Figures 9 and 10 illustrate EnPI profiles at two liquid-to-solid (L/S) ratios (0.18 and 0.30). Increasing the L/S ratio substantially elevates energy demand to achieve comparable moisture levels, reflecting the additional energy required to evaporate the higher initial moisture load.

Unlike conventional EnPIs that normalise energy consumption against total production output (e.g. kWh per unit produced) or general process services (e.g. kWh per unit heated), this EnPI directly links energy use to residual moisture – the unremoved portion of the drying target. This approach is particularly insightful for drying operations, where moisture removal is the key performance objective, and allows finer resolution of efficiency trends specific to product and batch conditions. However, it also underscores the need for careful normalisation when comparing across different formulations or campaigns with varying initial moisture levels.

Rooted in energy-balance principles, the EnPI quantifies the efficiency of energy transfer for moisture removal and provides a basis for statistical monitoring. Linear regression was used to evaluate the correlation between energy consumption and residual moisture, with R^2 serving as the key indicator of performance stability. High R^2 values (0.9341 for L/S = 0.18 and 0.9447 for L/S = 0.30) confirm strong linearity, indicating consistent process-energy behaviour across operating conditions. Extrapolated trends suggest theoretical energy requirements of ~996 kWh (L/S = 0.18) and ~1429 kWh (L/S = 0.30) to achieve zero

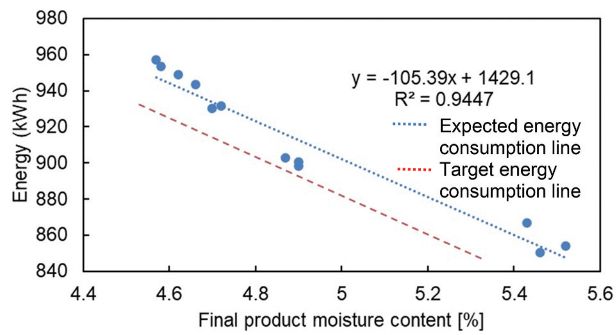

Figure 10. Relationship between energy consumption and final product moisture content for the DiPP fluidised bed dryer at a starting liquid-to-solid (L/S) ratio of 0.30.

residual moisture – values that are not practically targeted but highlight the influence of initial moisture loading on energy demand.

These EnPI findings complement earlier sensitivity analyses by identifying drying air temperature and initial moisture content (L/S ratio) as dominant energy drivers, reinforcing the tradeoff between moisture reduction and energy cost. Improving efficiency therefore requires strategies such as enhanced dryer insulation or optimised air distribution to minimise energy losses while maintaining target product quality. The EnPI also provides the baseline for subsequent CUSUM-based monitoring, enabling realtime detection of deviations from expected energy – moisture behaviour and supporting predictive process control of the digital twin of the physical twin.

CUSUM analysis

The CUSUM values were calculated by sequentially summing the differences between measured and expected energy values across consecutive runs (Table 5):

$$CUSUM_i = CSUM_{i-1} + \left(E_{actual,i} - E_{Expected,i}\right) \qquad 11$$

Plotting these cumulative deviations over time highlights sustained shifts in energy performance that are not immediately apparent in raw data. Downward trends indicate energy usage below the expected baseline (better-than-predicted efficiency), while upward trends signify excess energy consumption relative to predicted values.

Figure 11 presents CUSUM profiles for both L/S = 0.18 and L/S = 0.30. At L/S = 0.18, energy consumption initially falls below expected values, dropping from +12 kWh to −20 kWh by run 4 and reaching a minimum of approximately −39 kWh around runs 7–9. This indicates a consistently better-than-expected energy performance, particularly at drying air temperatures of 40–60°C. However, at 70°C, energy consumption shifts upward by 9–12 kWh above the baseline, revealing inefficiencies at higher temperatures.

Table 5. Actual energy consumption vs expected energy consumption of the FBD operated at L/S of 0.18 and 0.30.

		L/S=0.18		L/S=0.30	
Run	T (°C)	Actual energy consumption (kWh)	Expected energy consumption (kWh)	Actual energy consumption (kWh)	Expected *energy* consumption (kWh)
1	40	525.91	513.10	866.71	856.83
2		579.94	585.50	850.24	853.67
3		589.21	603.02	854.20	847.35
4	50	607.64	619.03	898.10	912.69
5		618.87	626.65	900.73	912.69
6		615.40	625.88	902.88	915.85
7	60	631.48	633.50	930.33	933.77
8		643.11	641.12	931.77	931.66
9		637.41	638.08	943.66	937.98
10	70	663.98	653.31	948.94	942.20
11		662.62	647.98	953.41	946.41
12		655.78	644.17	956.98	947.47

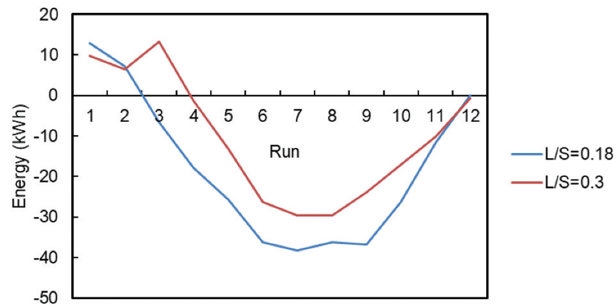

Figure 11. CUSUM profiles of energy consumption for the DiPP fluidised bed dryer at L/S ratios of 0.18 (blue) and 0.30 (red), illustrating cumulative deviations from the energy performance Indicator (EnPI) baseline. Negative trends indicate better than expected energy performance at 40–60°C, while upward shifts at 70°C highlight increased energy demand and reduced efficiency.

For L/S = 0.30, the cumulative sum follows a similar but less pronounced trajectory, declining from +10 kWh to approximately −30 kWh by runs 7–8 before returning towards zero. Greater variability is observed during initial runs at 40°C, consistent with earlier cell-temperature analyses showing increased drying heterogeneity under high moisture conditions. This variability diminishes at 50–60°C, where energy consumption remains below baseline, before rising sharply again at 70°C.

Overall, the CUSUM analysis reinforces earlier findings: lower drying temperatures (40–60°C) and lower initial moisture loads (L/S = 0.18) provide the most energy-efficient operating window, while 70°C consistently results in excess energy usage. This study demonstrated that integrating CUSUM-based energy performance analysis into the cyber-physical systems is essential for closing critical monitoring gaps, as CUSUM uniquely detects subtle and sustained performance abnormalities that the digital twin alone cannot capture; this integration not only enables real-time optimisation and robust anomaly detection but also significantly enhances the overall diagnostic and predictive capabilities of the digital twin in continuous drying process.

Conclusions

Traditional operational optimisation in pharmaceutical manufacturing, often reliant on static models or periodic data reviews, struggles to capture the dynamic and intertwined effects of human and machine behaviours on process efficiency and product quality. This study introduces a novel framework that overcomes these limitations by integrating realtime inline data, CUSUM analysis, and a mechanistic Digital Twin (DT) into a unified strategy for energy efficiency optimisation of the process.

The DT developed in gPROMS, successfully modelled the complex interactions governing the segmented FBD, enabling precise identification of parameters most critical to energy performance and drying quality. Building on this digital foundation, CUSUM analysis provided a transformative layer of sensitivity, detecting subtle yet impactful deviations in energy – moisture behaviour that the DT alone could not reveal. This combined approach pinpointed 60°C as the most energy-efficient operating temperature across L/S ratios of 0.18 and 0.30, with recommendations to further refine optimisation within the 50–60°C range.

This research marks a paradigm shift in pharmaceutical process optimisation: moving beyond equipment-centric control to a holistic, data-driven framework that accounts for both mechanical variability and human interactions. Such an approach has the potential to significantly reduce energy consumption, minimise waste, and enhance product consistency, delivering tangible cost and sustainability benefits. Moreover, the ability to detect deviations in real time empowers operators to make proactive interventions, safeguarding product quality and optimising resource utilisation.

The industrial implementation of this framework could follow a clear pathway: first, establishing a robust baseline Energy Performance Indicator (EnPI) model from historical or DT data; second, integrating the CUSUM monitoring algorithm into existing process control systems to track real-time deviations from this baseline; and finally, defining specific alert thresholds to trigger automated alarms or guide operator intervention.

Despite its contributions, this study has limitations that warrant future work. The identified optimal conditions are specific to the scale, design, and material properties of the investigated dryer and require validation against industrial-scale datasets to ensure broader applicability. Furthermore, while the analysis captures machine-driven deviations, a deeper integration of human-factor modelling within the DT could yield richer insights into operator-driven inefficiencies. Expanding the parameter space to include additional variables and higher-order interactions, alongside embedding automated root-cause diagnosis into the CUSUM framework, would further enhance predictive and prescriptive capabilities.

Bottom line, this research demonstrates that closing critical gaps in realtime monitoring and unlocking new opportunities for energy-efficient, quality-driven process control demands the seamless integration of advanced methodologies, an approach pivotal to realising the next generation of pharmaceutical manufacturing.

Nomenclature

Acronym	Definition
DT	Digital Twin
DiPP	Diamond Pilot Plant
FBD	Fluidised bed dryer
L/S	Liquid to solid ratio
CUSUM	Cumulative Sum

Symbol	Definition
λ	Latent heat of water
$C_{p.dry\,solid}$	Specific heat capacity of the powder blend
T_{gi} and T_{gf}	Initial and final temperature of granules
$\dot{m}_{water,in}$ and $\dot{m}_{water,out}$	Initial and final mass of water
$\dot{m}_{solid,dry}$	Total mass of material to be dried

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Data availability statement

The data that support the findings of this study are openly available in ORDA at https://doi.org/10.15131/shef.data.28741406.v1, reference Zandi, Mohammad (2025). CUSUM analysis of Fluidised Bed Dryer of Continuous Pharma Tablet Line. The University of Sheffield.

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