Deconstruction of Operational Variability in Biomass Production: An Application of Lean Six Sigma and System Dynamics

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ABSTRACT

Purpose: This study seeks to optimise key production parameters for biomass pellets by employing Lean Six Sigma (LSS) alongside dynamic system simulation. Emphasis is placed on fine-tuning moisture content, durability, and pellet diameter to meet international quality standards and performance operational.

Methodology/Approach: The research integrates DMAIC methodology with dynamic simulation modelling, analysing and optimising drum speed, material feed rate, and drying temperature via factorial design and system dynamics.

Findings: Implementing LSS markedly reduced moisture variability, hitting a stable mean of 9.446% and cutting defects down to 59,000 PPM. Durability saw a notable lift from 91.976% to 95.896%, with defects slashed by 80%. Pellet diameter was fine-tuned from 7.241 mm to 7.051 mm, bringing defects down to 45,000 PPM. Taken together, these results tick all the boxes for international standards and show considerable gains in process performance.

Research Limitation/Implication: The study is limited to one biomass site, focusing on key quality parameters. Future research could assess scalability and suitability across other renewable energy sectors.

Originality/Value of paper: This research highlights the novel integration of Lean Six Sigma and dynamic simulation in biomass pellet production, providing a robust framework for quality and operational stability in energy.

Category: Research paper

Keywords: lean six sigma; system dynamics simulation; defect reduction; biomass quality control

Research Areas: Quality Engineering, Quality Management

1 INTRODUCTION

In recent years, companies have placed operational efficiency, cost-cutting, and overall performance at the top of their agenda, driving uptake of methods like Green Lean and Six Sigma. In this vein, Gholami et al. (2021) devised a Green Lean Six Sigma approach for cleaner production using the DMAIC (Define, Measure, Analyse, Improve, Control) framework, one of Six Sigma's flagship methods, achieving tangible results with chemical and energy consumption dropping by 28% and 21%, respectively. Echoing this, r et al. (2014) affirm that Six Sigma offers a systematic, statistically robust route to enhancing product quality, innovation, and customer satisfaction. Similarly, Deeb et al. (2018) underline the need to scrutinise DMAIC outcomes phase-by-phase with SME-tailored checklists to keep management on track. Lastly, Tenera and Pinto (2014) illustrate how fusing DMAIC with project management pinpoints key problems, sets out clear improvement actions—such as the 24 steps they advocate—and ensures lasting operational benefits.

The Six Sigma (SS) methodology has found traction across diverse fields, delivering impressive process enhancements. In clinical chemistry, it has proven its mettle by optimising assays to five- and six-sigma quality standards. Ren et al. (2023), for instance, documented a notable leap of 46.8% in process cycle efficiency (PCE) after embracing Kaizen’s continuous improvement approach. Additionally, their study reported a 27.9% drop-in turnaround time, a 59.3% uptick in value-added activities, and a hefty 71.9% cut in non-value-added tasks after rolling out Lean Six Sigma (LSS). Likewise, Liu (2006) effectively employed SS to sharpen internal quality control (IQC) for biochemical assays, slashing cycle times and clocking up total savings of 76.6% (42,239 hours). In a similar vein, Ahmed et al. (2021) harnessed Six Sigma in clinical labs to pinpoint, rectify, and monitor errors, especially under critical circumstances like the COVID-19 pandemic, achieving a defect rate drop from 0–0.27% pre-pandemic to 0–0.13% during the pandemic.

Six Sigma has played a pivotal role in cutting down delays in lung cancer diagnoses by pinpointing key issues such as skipped regular check-ups, patient anxiety, and general reluctance to seek timely medical attention (Çelik et al., 2016). Further, Al-Zuheri et al. (2021) underline how this methodology enables thorough phase-by-phase result evaluations, bolstering organisational efficiency. They also stress using tailored checklists suited to SMEs, giving managers a leg-up in enhancing both organisational effectiveness and patient safety.

In manufacturing, Jitsamruay et al. (2023) fine-tuned medium-density fibreboard (MDF) production, chiefly by trimming variability in internal bonding (IB). Using a 25-2 factorial experiment (Resolution III), they pinpointed optimal settings for glue, heat, and pressure, directly affecting the IB of the finished product. Their results showed that targeted tweaks to glue, heat1, and PrimCirIn could hit an optimal IB of 0.7, or even reach 1.27, depending on production aims. Meanwhile, Antosz et al. (2022) leveraged Six Sigma to smarten up sustainable maintenance, boosting machine uptime and ironing out process hiccups. Likewise, Bloj et al. (2020) demonstrated how systematically applying Six Sigma—spotting core issues, tightening procedures, and chasing clear goals—catapulted a firm's update rate from 2.6% to 20% in just three months, comfortably beating their 10% target, chiefly through sprucing up internal processes and sharpening customer service.

Daniyan et al. (2022) illustrate how Six Sigma effectively tackles issues tied to sluggish productivity and efficiency through methods such as Kaizen and work standardisation. Their study bumped process cycle efficiency (PCE) up from 19.9% to 66.7%, a sizeable improvement of 46.8%, specifically in bogie car assembly. Consequently, lead time fell dramatically from 623,519.97 minutes to 449,280 minutes—a tidy 27.9% reduction—while value-added time rose significantly from 125,828.8 to 309,600 minutes, reflecting a 59.3% boost. Likewise, Altuğ (2023) applied Six Sigma within a screw-and-nut manufacturing firm, successfully cutting annual costs by roughly $21,780 and saving an additional $30,000 in losses by sorting out coating defects. Ultimately, coating thickness efficiency climbed impressively from 85% to 95%, hitting close to the sweet spot of 95%–97%.

In the iron ore industry, robust process capability is vital for keeping operations ticking over. Indrawati and Ridwansyah (2015) employed DMAIC to tackle operational issues head-on, redesigning duct dust collectors, standardising procedures, introducing vibrometers, and installing a nitrogen plant. Their study revealed a quality performance of 2.97 sigma, pinpointing 33.67% of activities as non-value-added, with a further 14.2% deemed unnecessary. Similarly, Nithyanandam and Pezhinkattil (2014) harnessed Six Sigma in precision machining of aerospace-grade 6061 aluminium, using two-way ANOVA to nail down key variability factors. They found optimal machining stability with spindle speeds set at 6000 RPM and feed rates at 3.4 mm/sec.

In innovation circles, blending Six Sigma with Lean Manufacturing has become standard practice, especially when fused with Industry 4.0 and circular economy concepts, proven to sharpen processes and enhance sustainability (Skalli et al., 2022). Similarly, Six Sigma has found its niche in modern manufacturing—particularly additive manufacturing (AM)—to nail process optimisation and get products right first-time round (Sithole et al., 2021). Moreover, Byrne et al. (2021) adopted a tailored Lean Six Sigma (LSS) approach in a pharmaceutical plant making acetaminophen tablets, grappling with delivery lags due to heightened demand amid the COVID-19 pandemic. Using a targeted seven-step strategy, they stripped out waste and tightened procedures, achieving impressive gains: an 84% cut in packaging backlog, 8.3% shorter batch cycles, 25% faster line changeovers, an 11% uptick in line availability, factory delivery times slashed by 69%, and value-added time boosted by 14%.

Lean Six Sigma (LSS) has gained traction globally, though its use in niche areas like biomass manufacturing remains thin on the ground. This gap underscores a clear need for further inquiry into its status and untapped opportunities within this field. Addressing this, the present study employs the classic DMAIC framework (Define, Measure, Analyse, Improve, Control), targeting waste reduction and incorporating an innovative dynamic simulation approach. The research homes in on improving productivity, moisture consistency, durability, and pellet diameter, demonstrating how a structured LSS application can significantly boost operational performance.

2 METHODOLOGY

The biomass firm faced quality snags in pellet production, stemming from poor control of moisture, diameter, and durability, which knocked customer satisfaction and put the company on the back foot. Its primary client, a government body using the pellets to fire boilers, insisted on strict adherence to the U.S. Pellet Fuel Institute (PFI) standard.

2.1 Methodological strategy

The study follows the DMAIC methodology (Figure 1), kicking off with the Define phase and weaving in dynamic simulation modelling. At this stage, customer requirements and expectations were mapped out clearly, setting the scene for biomass standards, assessing process performance, and gauging its predictive capability.

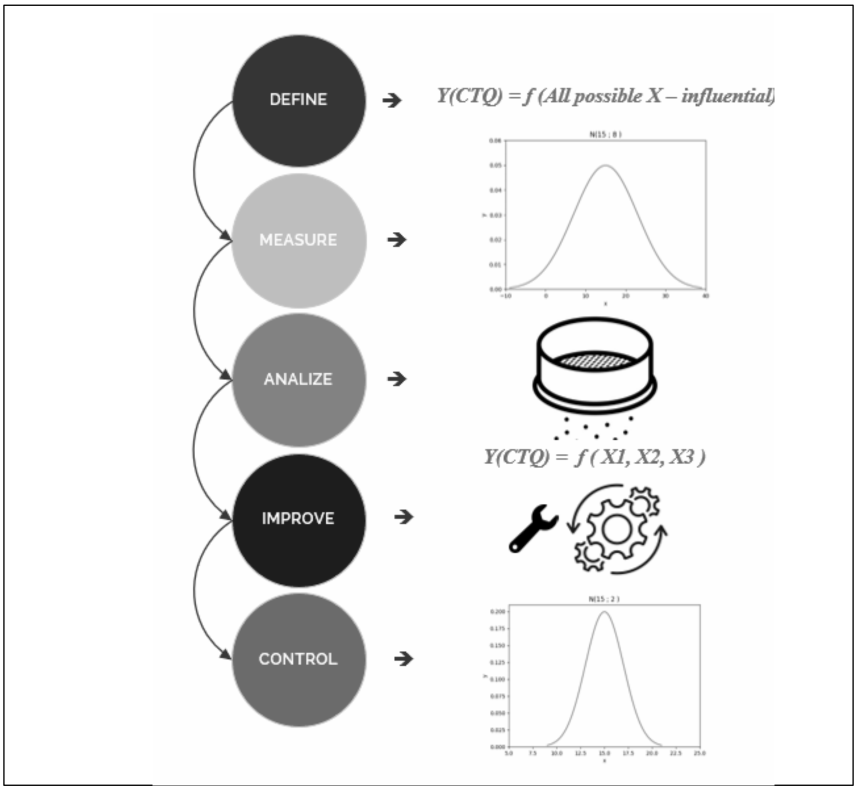

Figure 1 – Structured process flow of the DMAIC approach in Lean Six Sigma applications

Customer needs were pinpointed and tracked using the "Voice of the Customer" (VoC) approach, establishing Critical-to-Quality (CTQ) parameters to steer the project's aims. A dedicated team then set up a formal project plan, complete with timeline and budget. Statistical methods were deployed during the measurement phase to assess CTQ parameters, constructing a detailed process map pinpointing key inputs (labelled X_1, X_2, X_3, ... Xn) affecting quality. To ensure data was on the mark, a robust collection plan incorporating Measurement System Analysis (MSA) was developed, culminating in a solid baseline for performance and capability.

In the analysis phase, the team sifted through data on previously measured process variables, aiming to nail down root causes and validate their impact on critical quality outcomes. During the improvement stage, potential enhancements were spotted and ranked, with redesign initiatives implemented and validated via experimental design. Finally, the control phase cemented long-term gains by rolling out standardised processes, employee training, and ongoing monitoring through control charts and statistical techniques. The next section dives deeper into these stages.

3 RESULTS

3.1 Define phase

The company supplies its wood-waste pellets in 15 kg packs, with 60% of output heading to a government client demanding rigorous compliance with PFI standards—moisture content spot-on, pellet diameter within 6–7 mm, durability no less than 95%, and length under 38 mm. The manufacturing runs from raw-material intake through to storage. Data revealed 85% of customer gripes were down to excess moisture, inconsistent diameters, and insufficient durability. Meeting international standards (as summarised in Table 1) is thus crucial. The research team pinpointed critical process variables—including conveyor belt speed and drying temperature—that significantly influenced moisture content, pellet diameter, and mechanical robustness.

Table 1 – Benchmark standards for biomass pellet quality parameters

Standard	**Moisture Content (%)**	**Ash Content (%)**	**Bulk Density (kg/m³)**	**Heating Value (MJ/kg)**	**Mechanical Durability (%)**	**Diameter (mm)**	**Length (mm)**
PFI (EE.UU.)	≤ 10% (Premium), ≤ 12% (Standard)	≤ 1% (Premium), ≤ 2% (Standard)	≥ 640	≥ 19	≥ 96.5% (Premium), ≥ 95% (Standard)	6 a 8	≤ 38
CEN/TC 335 (Europa)	≤ 10% (Clase A1 y A2), ≤ 12% (Clase B)	≤ 0.7% (A1), ≤ 1.2% (A2), ≤ 2% (B)	600-750	≥ 16.5 (4.6 kWh/kg)	≥ 97.5% (A1), ≥ 96.5% (A2 y B)	6 ± 1 o 8 ± 1	≤ 40
ONORM (Austria)	≤ 10%	≤ 0.5%	≥ 600	≥ 18	≥ 97.5%	6 a 8	≤ 40

Standard	Moisture Content (%)	Ash Content (%)	Bulk Density (kg/m³)	Heating Value (MJ/kg)	Mechanical Durability (%)	Diameter (mm)	Length (mm)
Pellsam (Suecia)	≤ 10%	-	-	-	-	-	-
DIN 51731 (Alemania)	≤ 12%	≤ 0.5%	≥ 600	≥ 18	≥ 97.5%	6 a 8	≤ 40
SN 166000 (Suiza)	≤ 10%	≤ 0.7%	≥ 600	≥ 17.5	≥ 97.5%	6 a 8	≤ 40

3.2 Measure phase

The biofuel manufacturing process kicks off with the intake and moisture inspection of wood-waste raw material, which is then stored. Depending on moisture levels, drying drum parameters are fine-tuned before loading the material into the drum. Post-drying, wood chips move to Silo No. 01 for another moisture check, then are chipped into sawdust and stored in Silo No. 02 after a further moisture inspection. The sawdust proceeds to pelletising, and after screening, pellets enter Silo No. 03 for final moisture and diameter checks ahead of packaging. Lastly, the pellets head off to the finished-goods warehouse. These steps are neatly summed up in Figure 2.

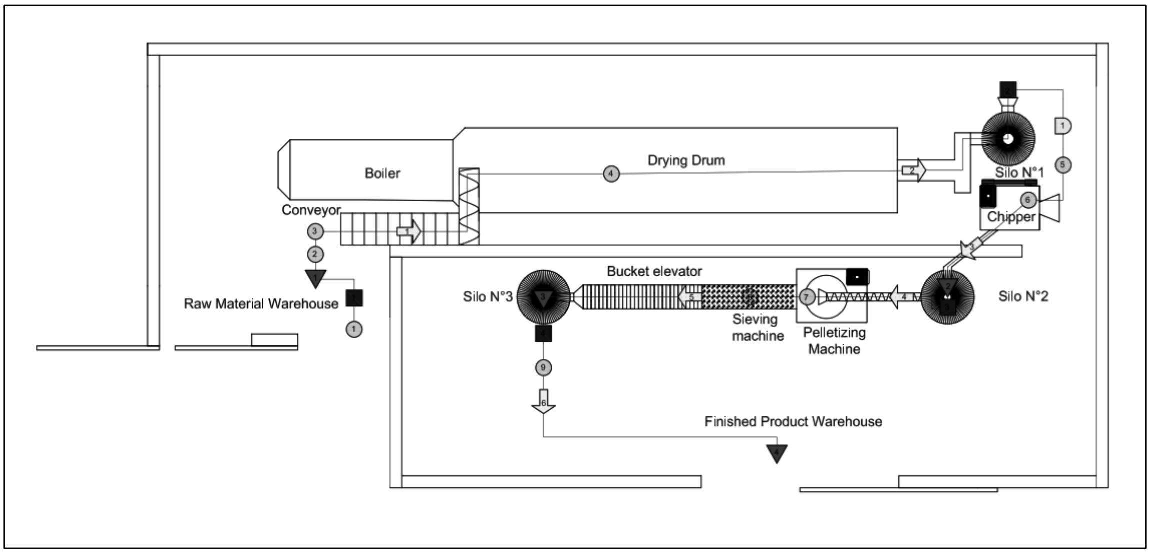

Figure 2 – Systematic representation of the biomass pellet manufacturing workflow.

Pellet moisture content was measured at ambient temperature in the packaging area using the PCE-WT1N meter, compliant with CEN/TC 335 and PFI standards. Mechanical durability was assessed via the Holmen NHP200 tester following EN 15210-1. Pellet diameter was checked with Vernier calipers, also adhering to CEN/TC 335. Weekly production totalled 13,500 kg in 15 kg bags, with random sampling at 158 for moisture and diameter and 85 for durability, ensuring accuracy. Key statistics are summarised in Table 2. Moisture (mean: 9.715%) and durability (mean: 91.976%) followed a normal distribution, showing minimal variability (CV: 8.5% and 3.6%).

Table 2 – Statistical distribution characteristics of moisture, durability, and diameter variables

	Moisture Percentage (%)	**Durability (%)**	**Diameter (mm)**
Sample Size	158	50	158
Mean	9.715	91.976	7.241
Standard Deviation	0.830	3.341	0.745
Minimum	7.950	84.999	6.020
25th Percentile	9.133	89.492	6.603
Median	9.700	92.363	7.160
75th Percentile	10.258	94.680	7.933
Maximum	11.900	99.854	8.460
p-value for normality	0.198	0.7505	0.000

The data for wood pellets clearly indicates substantial shortcomings in quality control, notably concerning moisture and durability. Moisture content—set between 9% and 10%, targeting 9.7%—demonstrated poor capability (Pp=0.2), well below par, suggesting the process often drifted outside specified limits. Durability was even more problematic, registering a shocking 8,413,605.75 PPM beyond acceptable standards, with a negative Ppk (-0.25) reflecting serious control issues. Conversely, pellet diameter fared slightly better (Ppk=0.61), yet still showed considerable room for improvement, with 221,518.99 PPM falling short of the required 6–8 mm specification. A Johnson transformation was applied for diameter, whereas moisture and durability were analysed assuming normality.

Table 3 – Process capability index summary for critical quality parameters in measurement phase

Description	**Moisture percentage (%)**	**Durability (%)**	**Diameter (mm)**
LSL (Lower Specification Limit)	9	94.5	6
Target	9.7	96	7
USL (Upper Specification Limit)	10	97	8
Sample Mean	9.715	91.976	7.241
Sample Size	158	50	158
Std. Dev. (Long term)	0.830	3.341	0.745

Description	**Moisture percentage (%)**	**Durability (%)**	**Diameter (mm)**
Std. Dev. (Short term)	0.80318	3.66234	-
Observed Performance (Long term)	151898.73	7400000	0
Expected Performance (Long term)	194368.22	775308.03	0
Expected Performance (Short term)	186162.8	754686.81	0
PPM < LSL	500000	600000	221518
PPM > USL	560077.59	6322.71	214735
Total PPM	548056.3	841360.75	221518
Capability (Pp)	0.2	0	0
Capability (PPL)	0.29	0	0
Capability (PPU)	0.11	0	0
Capability (Ppk)	0.11	-0.25	0.61

Control of moisture percentage was found to be steady, as depicted in Figure 3, with all points comfortably within the control limits (UCL=12.125, LCL=7.306). No irregularities cropped up, nor did any worrying patterns emerge, settling around a mean of 9.715 and a well-behaved moving range.

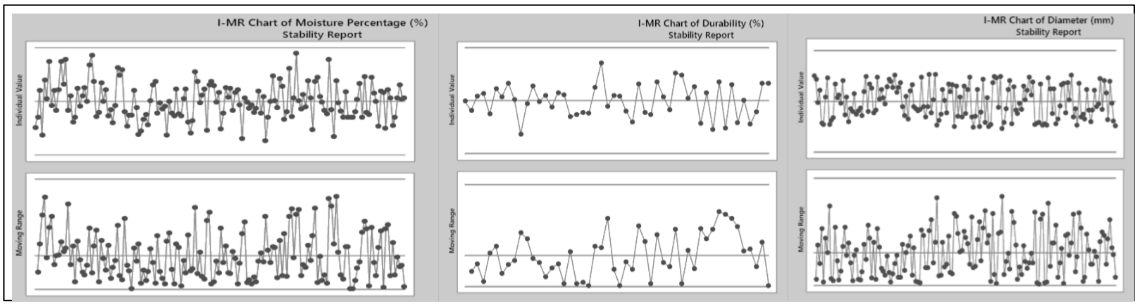

Figure 3 – Statistical control charts for critical quality attributes during measurement phase.

The durability analysis likewise revealed a stable process, comfortably within control limits (UCL=102.96, LCL=80.99), centring around a mean of 91.975. No points wandered out of control, and fluctuations fell within the realm of natural variation, despite some notable wobble in the moving range. Similarly, the diameter proved consistently stable, averaging 7.241 mm, neatly contained between the established control limits (UCL=9.539, LCL=4.942). A low moving range averaging 0.864 reinforced the impression of a tightly controlled process.

3.3 Analyse phase

The phase kicked off with the research team gathering to pinpoint likely culprits behind variations in critical quality characteristics and to suss out reasons for the previously noted lack of capability. Employing the 6M methodology, an Ishikawa diagram (Figure 4) was drafted to neatly capture variables affecting moisture content. The same approach was rolled out for other parameters, offering clarity on the sources of variability.

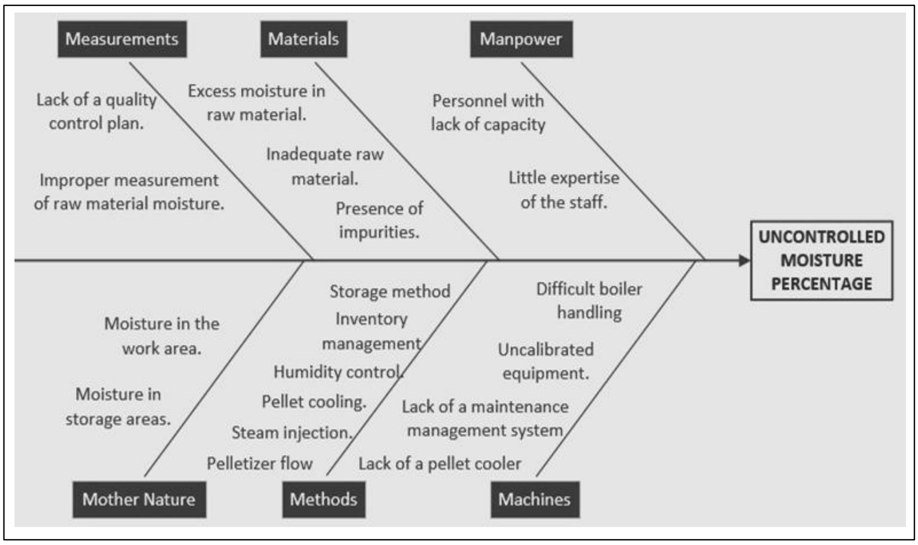

Figure 4 – Pareto analysis of predominant causes contributing to moisture variability

Ten variables (X) potentially impacting moisture content were flagged up, with the key players selected using a Pareto chart (see Table 4). Consequently, nine root causes surfaced, warranting a deeper look to fully grasp their knock-on effects.

Table 4 – Pareto analysis of predominant causes contributing to moisture variability

N°	Cause	Percentage	Accumulated percentage
1	Drying speed	10	10
2	Raw material feeder belt speed.	10	20
3	Speed of entry of raw material to the pellet mill	10	30
4	Raw material moisture control	10	40
5	Inventory management	9	49
6	Storage method	8	57
7	Excess moisture in the raw material	8	65
8	Inadequate raw material	8	73
9	Drying temperature	4	77

Variables suitable for parametrisation within the pelletising kit were picked out, with five key factors scrutinised: raw material moisture percentage (X_1), conveyor belt speed (X_2), dryer drum speed (X_3), drum temperature (X_4), and material input speed (X_5), all bearing directly upon moisture content (see Table 5).

Table 5 – Process variables assessment for moisture content control in pellet manufacturing

Batch	**Raw material moisture percentage - %**	**Conveyor belt speed - rpm**	**Dryer drum speed - rpm**	**Drum temperature - °C**	**Material entry speed - rpm**	**Average moisture percentage**
	(X1)	(X2)	(X3)	(X4)	(X5)	(Y1)
1	40	28.45	19.46	120	14.25	10.51
2	46	25.56	18.06	115	10	10.64
3	37	28.45	19.46	130	12.89	10.59
4	25	34.54	22.07	140	16.46	10.16
5	19	36.02	24.26	150	18.5	9.94
6	32	31.27	20.85	125	15.75	10.37

Correlations with ρ values ranging from 0.68 to 0.90 were assessed to size up the statistical links between the variables and the critical quality characteristic (see Figure 5). This analysis proved useful in pinpointing and ranking the key ingredients shaping product quality.

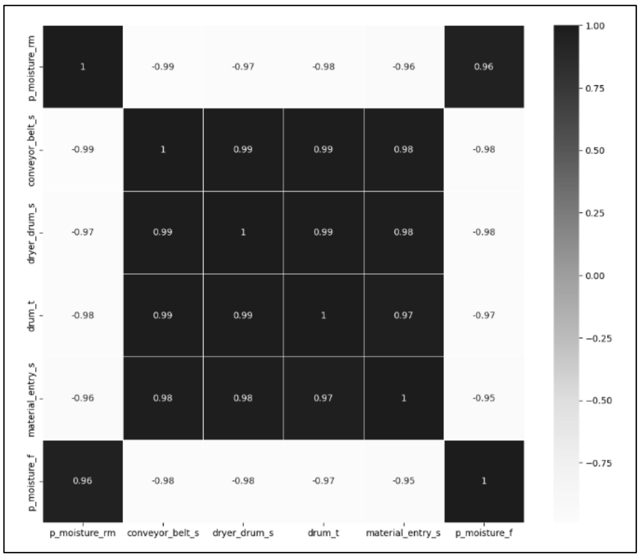

Figure 5 – Correlation heat map of process parameters with critical quality characteristics

In the same vein, correlations among the remaining variables were worked out. Building on these results, multiple linear regression models were knocked together for the three quality variables, as set out in Table 6.

Table 6 – Statistical modelling equations for process parameter optimization

Equation	R^2	MSE
Average moisture percentage = 10.2541 + - 0.2009 * p moisture rm - 0.4949 * conveyor belt s - 0.1251 * dryer drum s - 0.0025 * drum t + 0.0988 * material entry speed (1)	0.650	0.0071
Durability (%) = 56.11 - 0.1643* moisture percentage raw material + 0.9991* dryer drum speed (2)	0.758	0.3589
Diameter (mm) = 3.4011 + 0.001073 drum temperature + 0.24959 * material input speed (3)	0.663	0.0034

Raw material moisture (X_1), conveyor belt speed (X_2), dryer drum speed (X_3), pelletiser sawdust feed rate (X_4), and internal drum temperature (X_5) emerged as the critical process parameters pulling the strings for the three variables discussed in the earlier models.

3.4 Improve phase

3.4.1 Improvement of moisture percentage

In the improvement phase, changes were proposed to mitigate the effects resulting from the previously identified causes related to biomass moisture.

Implementation of a 2^4 factorial design.

For the improvement, a 2^4 factorial design was conducted with four factors, each at two levels, and two runs were performed for each combination. The levels were based on the company's production standards and the equipment available. Table 7 organizes the information to identify the factor levels.

Table 7 – Factorial design configuration for parameter evaluation in moisture control

Typing	Key process parameter	Low level	High level
A	Raw material moisture percentage (X1)	19% (-1)	40% (+1)
B	Speed of the raw material feeding conveyor belt (X2)	28.45 rpm (-1)	36.02 rpm (+1)
C	Dryer drum speed (X3)	19.46 rpm (-1)	24.26 rpm (+1)
D	Material entry speed (X4)	8 rpm (-1)	13.4 rpm (+1)

In the development of the mathematical model, the previously established equation for a 2^4 factorial design was considered, as presented below in equation 4.

$$\begin{aligned} Y_{ijkl} = \mu + \alpha_i + \beta_j + \gamma_k + \delta_l + (\alpha\beta)_{ij} + (\alpha\gamma)_{ik} + (\alpha\delta)_{il} + (\beta\gamma)_{jk} \\ + (\beta\delta)_{jl} + (\gamma\delta)_{kl} + (\alpha\beta\gamma)_{ijk} + (\alpha\beta\delta)_{ijl} + (\alpha\gamma\delta)_{ikl} \\ + (\beta\gamma\delta)_{jkl} + Error_{ijkl} \end{aligned} \tag{4}$$

An analysis of variance (ANOVA) was performed to weigh up the significance of experimental factors, initially yielding an R^2 of 69.08%. After trimming away non-significant terms, the final model—focusing solely on the four key factors (A, B, C, D) for pellet production—was nailed down as shown in equation 5.

$$Y_{ijkl} = 10.2131 + 0.4375\, X_A + 0.75 X_B + 0.7375 X_C + 0.8375 X_D \tag{5}$$

The parameters required to achieve a quality target of 9% moisture in the biomass were determined using Equation 2. Based on this, Table 8 was generated, showing the equipment parameters according to the moisture content of the raw material. X_1 should range between 19% and 40%. The wood will be processed in five-ton batches.

Table 8 – Parameters defined according to the quality target

Raw material moisture percentage (X_1)	**Speed of the raw material feeding conveyor belt (X_2)**	**Dryer drum speed (X_3)**	**Material entry speed (X_4)**	**Moisture percentage (Y_1)**
19.0 – 20.0	31.48	21.38	12.05	9
20.1 – 21.0	32.24	21.86	10.97	9
21.0 – 22.1	31.48	21.38	11.78	9
22.2 – 23.1	30.72	20.90	12.59	9
23.2 – 24.2	31.48	21.38	11.51	9
24.3 – 25.2	30.72	20.90	12.32	9
25.3 – 26.3	30.34	22.10	11.24	9
26.4 – 27.3	30.72	21.14	11.78	9
27.4 – 28.4	31.48	21.62	10.70	9
28.5 – 29.4	30.72	21.14	11.51	9
29.5 – 30.5	29.96	20.66	12.32	9
30.6 – 31.5	30.72	21.14	11.24	9
31.6 – 32.6	29.96	20.66	12.05	9
32.7 – 33.6	31.10	21.15	10.7	9
33.7 – 34.7	30.34	20.66	11.51	9
34.8 – 35.7	31.10	21.14	10.43	9
35.8 – 36.8	30.34	20.66	11.24	9
36.9 – 37.8	30.72	21.38	10.16	9
37.9 – 38.9	30.34	20.66	10.97	9

Raw material moisture percentage (X_1)	**Speed of the raw material feeding conveyor belt (X_2)**	**Dryer drum speed (X_3)**	**Material entry speed (X_4)**	**Moisture percentage (Y_1)**
39.0 – 39.9	29.59	20.18	11.78	9
40	30.34	20.90	10.43	9

The material is accepted under the INEN 251 1977-02 standard, with a sampling quantity of 25 kg for every 30 tons. Sampling is performed in subgroups of three for testing. Materials are stored in a warehouse with a coding system that highlights the entry date.

Finished product storage policy

To optimize time within the organization, a coding system linked to the raw material was implemented, complemented by a storage policy based on the FIFO method for the final product. Storage spaces were organized using a colour scheme and the manufacturing date, facilitating both visual control and operational management. Product distribution was carried out in batches of 450 bags, each weighing 15 kilograms, minimizing moisture gain in the product. This was crucial, considering the city has an average annual relative humidity of 89%, with monthly fluctuations ranging between 87% and 91%.

3.4.2. Improvement of mechanical durability variable

The dynamic behaviour of biomass pellet durability was modelled as a function of two independent variables: raw material moisture and drum speed. The multiple regression equation underpinning this analysis is detailed in Table 7.

$$D(t) = 56.11 - 0.1643 \cdot M(t) + 0.9991 \cdot D(t) \quad (6)$$

The system dynamics include two key relationships: the evolution of raw material moisture and drum speed. The moisture changes according to:

$$\frac{dMoisture(t)}{dt} = -k * DrumSpeed(t) + b \quad (7)$$

Where:

k: Drum efficiency constant.

b: Natural moisture gain/loss rate.

Meanwhile, the drum speed is adjusted using a PI controller according to:

$$\frac{dDrumSpeed(t)}{dt} = K_p * e(t) * +K_i \int e(t)dt \quad (8)$$

Where:

Kp: Proportional gain.

Ki: Integral gain.

The drum speed is dynamically adjusted through a proportional-integral (PI) controller based on the error between the current durability and the target:

Data shows that 85% of complaints were related to excessive moisture content, variable diameters, and insufficient mechanical durability. It was determined that compliance with international standards, shown in Table 1, is necessary to meet customer needs. The research team identified key process.

$$e(t) = \mathrm{TargetDurability} - \mathrm{Durability}(t) \tag{9}$$

Here, $e(t)$ is the error defined as the difference between the target durability (96%) and the current durability. The system ensures that, regardless of initial conditions, durability converges towards the target. The dynamic representation of the control system is shown in Figure 6, illustrating the relationship between the variables.

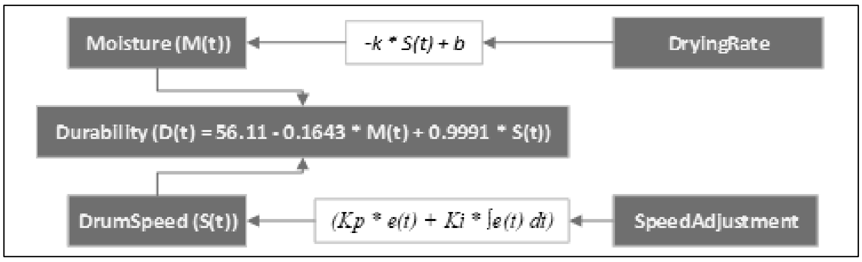

Figure 6 – Diagram of dynamic relationships representing the interaction between key variables affecting biomass

Following the development of simulation models, results are presented in Figure 7, illustrating the progression of biomass pellet durability across 25 scenarios with varying initial moisture and drum speed conditions. The 96% quality target was met in most cases, with curves stabilising around the target within 20 to 30 hours. This suggests the system responds promptly and effectively, even when faced with notable initial variations.

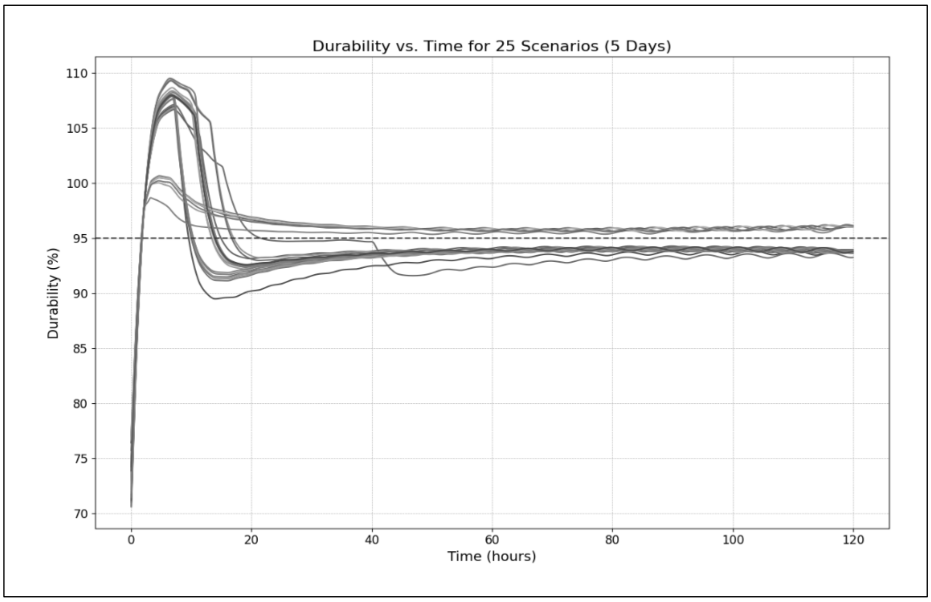

Figure 7 – Dynamic system simulation for durability with 25 scenarios

Once initial oscillations settled, durability curves exhibited marked stability around the 96% target. Minor residual variations, deemed typical, likely stemmed from differences in initial conditions or slight imperfections in controller tuning. This behaviour underscores the robustness of the dynamic model and PI controller in steering the system towards the desired quality state across diverse initial scenarios.

Sensitivity analysis and simulation across 25 scenarios pinpointed the optimal PI controller parameters for minimising deviations from the 96% target: proportional gain for drum temperature (KTp) at 1.0, integral gain (KTi) at 0.2, proportional gain for material input speed (KVp) at 0.8, and integral gain (KVi) at 0.2. The best scenario began with initial conditions of 135.93 °C for drum temperature and 23.88 rpm for input speed, stabilising at 124.18 °C and 14.10 rpm, respectively, with an average deviation of 0.168% and a maximum of 2.51%. These parameters were configured into the equipment to safeguard the desired durability.

3.4.3. Improvement of diameter variable

The mathematical model used to estimate the diameter of biomass pellets is based on a multiple regression equation, describing the relationship between the diameter and two independent variables: the pelletizing drum temperature and the material input speed. The equation is:

$$\begin{aligned} Diameter(t) = 3.4011 + 0.001073 * DrumTemperature(t) \\ + 0.24959 * MaterialInputSpeed(t) \end{aligned} \tag{10}$$

To simulate the evolution of diameter over time, the independent variables drum temperature and material input speed were dynamically modelled using proportional-integral (PI) controllers.

The drum temperature is dynamically adjusted to minimize the error:

$$\frac{dDrumTemperature(t)}{dt} = K_{Tp} * e(t) + K_{Ti} * \int e(t)dt \tag{11}$$

Where:

KTp: Proportional gain of the PI controller for temperature.

KTi: Integral gain of the PI controller for temperature.

Similarly, the input speed is adjusted as:

$$\frac{dMaterialInputSpeed(t)}{dt} = K_{Vp} * e(t) + K_{Vi} * \int e(t)dt \tag{12}$$

Where:

KVp: Proportional gain of the PI controller for speed.

KVi: Integral gain of the PI controller for speed.

The diameter error $e(t)$ is a quantitative measure of the deviation between the current pellet diameter and the desired target.

$$e(t) = TargetDiameter - Diameter(t) \tag{13}$$

Similarly, dynamic system simulation is used for the product diameter variable, as shown in Figure 8, with the aim of identifying the parameters that ensure compliance with the established quality standard.

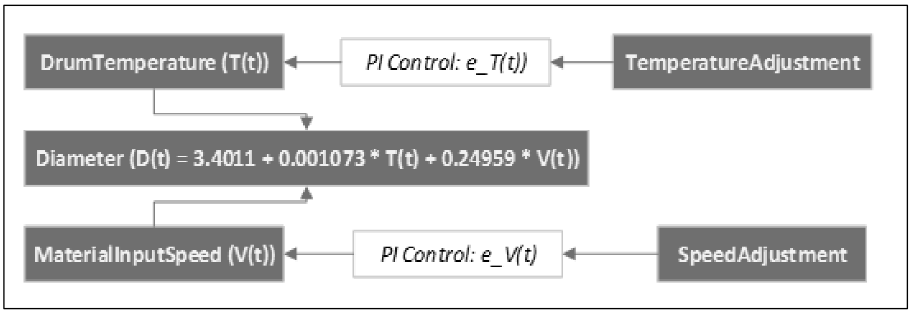

Figure 8 – Diagram of dynamic relationships representing the interaction between key variables affecting the diameter of biomass pellets

The model was evaluated using Python, with simulation outcomes presented in Figure 9, depicting the evolution of pellet diameter over time across 25 scenarios, accounting for initial variations in drum temperature and material input speed. The system aimed to stabilise the diameter at 7 mm, aligning with the desired quality standard. Simulations revealed that all trajectories converged towards this target following an initial adjustment period, confirming the system's capability to dynamically regulate variables and uphold quality standards.

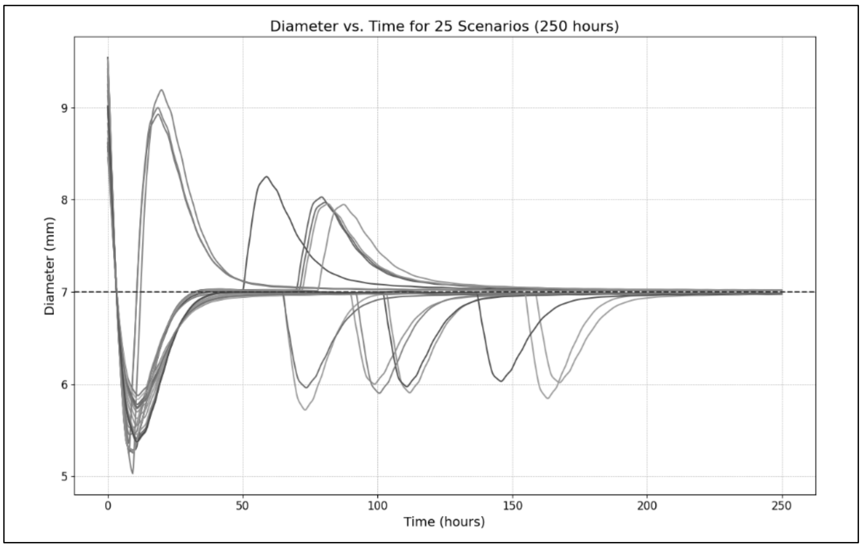

Figure 9 – Dynamic system simulation for diameter with 25 scenarios

During the first 100 hours, the curves exhibit significant oscillations, with diameter values exceeding 9 mm or falling below 5 mm in some cases. These initial oscillations result from aggressive adjustments by the PI controller, which seeks

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to quickly correct the error between the current diameter and the target. However, as time progresses, these oscillations are progressively dampened, demonstrating the controller's effectiveness in stabilizing the system.

The average stabilization time is approximately 150 hours, though some scenarios achieve stability around 100 hours while others require more than 200 hours. This variation in stabilization times suggests that certain initial conditions or controller configurations may influence the speed of adjustment. Despite these differences, all trajectories converge toward the target, demonstrating the robustness of the model and the system's ability to adapt to diverse initial conditions.

The analysis of scenarios for controlling pellet diameter revealed that the optimal PI controller parameters are: KTp=1.0, KTi=0.2, KVp=0.8, and KVi=0.2. The best scenario presented an initial drum temperature of 135.73 °C and an initial input speed of 19.68 rpm, reaching final values of 134.46 °C for temperature and 13.77 rpm for speed. The average deviation from the 7 mm quality target was 0.112 mm, with a maximum deviation of 1.459 mm. These results demonstrated that the tuned PI controller was robust and effective, successfully stabilizing the pellet diameter at the desired quality standard, even under variable initial conditions.

3.5 Control phase

The control phase assesses the outcomes of implemented changes and ensures their long-term sustainability. In the factory, the sampling plan was revised in line with the NTE INEN 1 233:95 standard. Twenty-one samples are collected per production batch on a weekly basis, divided into two subgroups. Data is securely stored in the company's database for subsequent analysis. The results are summarised in Table 9.

Table 9 – Post-implementation capability analysis of key quality metrics

Description	**Moisture percentage (%)**	**Durability (%)**	**Diameter (mm)**
LSL (Lower Specification Limit)	9	94.5	6
Target	9.7	96	7
USL (Upper Specification Limit)	10	97	8
Sample Mean	9.446	95.896	7.051
Sample Size	40	40	40
Std. Dev. (Long term)	0.424	0.566	0.618
Std. Dev. (Short term)	0.428	0.547	0.537
Observed Performance (Long term)	200000	6856	25000
Expected Performance (Long term)	241970.38	25647.60	75000
Expected Performance (Short term)	246739.85	32504.02	100000
PPM < LSL	125000	0	25249

Description	**Moisture percentage (%)**	**Durability (%)**	**Diameter (mm)**
PPM > USL	75000	50000	38556
Total PPM	200000	50000	106628
Capability (Pp)	0.39	0.74	0.54
Capability (PPL)	0.35	0.82	0.57
Capability (PPU)	0.44	0.65	0.51
Capability (Ppk)	0.35	0.65	0.51

The process capability analysis for moisture percentage shows a Ppk index of 0.52, indicating that the process is not fully centered or optimized relative to the 9.7% target. This suggests that a significant portion of production might be near the specification limits, although the sample mean of 9.446% reflects that the process consistently operates be-low the target. In terms of quality, the process's sigma level indicates high variability, generating approximately 59,000 PPM out of specification, primarily at the lower limit. How-ever, for the organization, no major changes are required due to the costs involved in in-creasing the sigma level.

The process capability for durability shows a Pp index of 0.41, reflecting a process that is not centered on the 96% target. While the sample mean of 95.896% is relatively close to the target, the low capability indicates that the process is not robust enough to consistently maintain values within specification limits. This results in approximately 100,000 PPM out of specification, mostly for values below the target. The process for pellet diameter shows a Ppk index of 0.65, indicating better performance compared to the other variables, but still insufficient to ensure high process capability. With a sample mean of 7.051 mm, the process operates slightly above the 7 mm target.

However, variability generates approximately 45,000 PPM out of specification, mostly due to values exceeding the upper limit. Additionally, control charts were applied to analyse the behaviour of key variables (see Figure 10). The moisture percentage control chart demonstrates a process under statistical control, with individual values fluctuating around the mean and staying within established control limits. Similarly, the moving ranges remain within their limits, indicating consistent variability between consecutive observations.

The durability chart also reflects a process under statistical control, with individual values centred around the mean and within control limits. In the moving range chart, consecutive differences remain within the limits, confirming process stability and con-trolled variability between measurements.

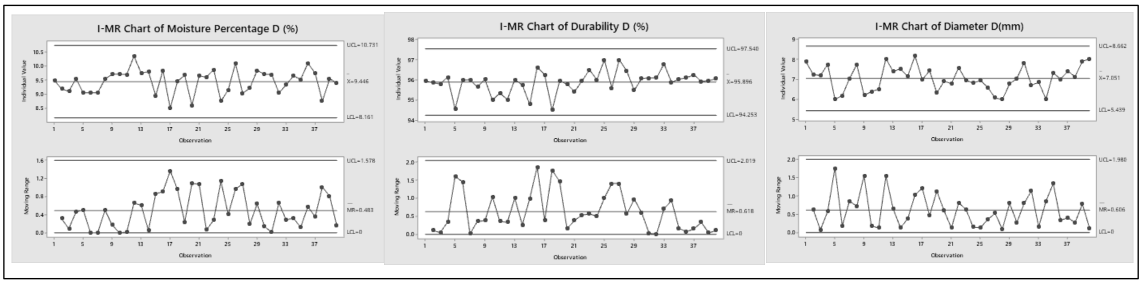

Figure 10 – Control charts for the three quality variables in the final stage.

Lastly, the I−MR chart for diameter reflects similar outcomes, with individual values consistently centred around the mean and within control limits. Likewise, the moving ranges display steady variability between consecutive observations, reaffirming the statistical stability of the process. These control charts confirm that all three variables exhibit controlled and predictable behaviour within the analysed system.

4 DISCUSSION

The implementation of Lean Six Sigma through the DMAIC methodology, coupled with dynamic systems simulation, led to notable improvements in process quality parameters. Moisture content decreased from an average of 9.715% to 9.446%, significantly cutting defects to 59,000 ppm, though further refinement is needed to align fully with the 9.7% target. Durability improved markedly, rising from 91.976% to 95.896%, with waste reduced from 500,000 ppm to 100,000 ppm—underscoring the effectiveness of control measures. Diameter was finely tuned, dropping from 7.241 mm to 7.051 mm, with defects reduced to 45,000 ppm.

Dynamic systems simulation enabled the modelling and prediction of process behaviour, optimising modifications to stabilise key variables and reduce variability. This approach pinpointed specific improvement opportunities, minimising waste and ensuring adherence to quality standards. Full implementation led to a marked reduction in accumulated waste, recovering thousands of units and enhancing system efficiency. Its practical value lies in the potential to replicate this process across other settings, precisely parameterising variables to optimise product quality. These findings confirm that combining Lean Six Sigma with dynamic systems simulation offers a robust framework for driving continuous improvement and operational sustainability. In conclusion, limited research has addressed the enhancement of quality characteristics in plant-based biomass, positioning this study as a noteworthy contribution to the field.

5 CONCLUSION

The implementation of Lean Six Sigma markedly reduced waste across key process quality variables. Applying the DMAIC approach, moisture defects dropped from 90,000 PPM to 59,000 PPM, durability defects from 500,000 PPM to 100,000 PPM, and diameter defects from 65,000 PPM to 45,000 PPM, yielding an overall improvement of over 450,000 PPM across the system.

Dynamic systems simulation enabled precise prediction and adjustment of critical parameters. By fine-tuning drum speed and raw material moisture, durability was stabilised at 95.896%, achieving an 80% reduction in related defects. This data-driven approach ensured optimal alignment with quality standards.

Beyond enhancing quality, the DMAIC methodology promoted efficient resource use. Reducing defects and waste led to the annual recovery of thousands of units, boosting profitability and lessening the environmental impact of out-of-specification products.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest. The funders had no role in the design of the study, in the collection, analyses, or interpretation of data, in the writing of the manuscript, or in the decision to publish the results.