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Integration of Statistical Process Control and Bayesian Network to Improve Diagnosis in Industrial Maintenance: application to a textile plant in Central Africa

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Integration of Statistical Process Control and Bayesian Network to Improve Diagnosis in Industrial Maintenance: application to a textile plant in Central Africa

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Authors contribution

NJEDOCK N. D. was assigned to the concep-tualisation of the project, writing, data reten-tion, and formal analysis. Meva'a L. R. J., Voufo J., Biyeme F., and YO J. D. were responsible for the methodology, review, editing, and validation.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Integration of Statistical Process Control and Bayesian Network to Improve Diagnosis in Industrial Maintenance: application to a textile plant in Central Africa

Abstract

Production downtime represents a major challenge for manufacturing companies, particularly in the African textile sector, where maintenance resources are limited. This study proposes an integrated approach combining Statistical Process Control (SPC) and Bayesian Networks (BN) to improve the diagnosis of the root causes of production downtime, as applied to machine RN073 at SITRACEL S.A., a company specializing in the manufacture of pocket tissues in Cameroon. The methodology is divided into four phases that form part of a continuous cycle. A Primary SPC assessment of the current state of operations based on data from February 2026 reveals that Non-Production Time (NPT) and Breakdown Time (BDT) are structurally out of statistical control, with respective averages of 18.4 and 12.43 min/h, well above the targets set at 2.07 and 1.20 min/h. Bayesian networks, constructed based on the machine's functional analysis, are then used to identify the dominant causes through sensitivity analysis: node A4 (Machine Breakdown) for NPT and station C3 (bending and cutting) for BDT. Targeted corrective actions produced measurable results: a Secondary SPC conducted in April and May 2026 revealed a 59% reduction in both indicators. These results demonstrate the added value

of Bayesian networks as a probabilistic diagnostic tool complementary to SPC, while helping to fill the gap in LSS literature regarding the African industrial context.

Keywords: SPC, BN, Maintenance diagnosis, NPT, BDT

Introduction

In an increasingly competitive industrial environment, controlling production downtime is a top strategic priority for any manufacturing company. The costs generated by unanticipated failures, such as; capacity losses, resource overconsumption, and quality degradation directly impact the competitiveness and profitability of production units. This reality is particularly acute in the African textile sector, where operational constraints and aging machinery amplify the vulnerability of maintenance systems to recurring failures. Although Statistical Process Control charts are robust for detecting out-of-control conditions, they remain limited tools for failure diagnosis, and alternative methods available are constrained in practical application by their dependence on practitioner expertise. In other words, knowing that a process is going off track is not enough: it is also essential to identify, with rigor and speed, why it is going off track. (Alaeddini and Dogan, 2011)

It is precisely this limitation that this study seeks to address. Statistical Process Control (SPC) is now widely recognized as a cornerstone of real-time industrial monitoring. In this context, He and Wang (2018) position it as a large-scale data analysis tool for smart manufacturing, outlining a roadmap of recent developments in statistical monitoring and identifying process-feature-based methods among the most promising for the next generation of industrial tracking. However, SPC alone does not answer the causal question. Bayesian Networks (BN), as probabilistic graphical models capable of reasoning under uncertainty for diagnosis or forecasting, naturally complement this framework. Ademujimi and Prabhu (2022) demonstrated that Bayesian Networks are a failure diagnostics tool particularly suited to smart manufacturing systems, with the ability to distinguish parent nodes from ancestor nodes in the causal structure, thus providing interpretable diagnostics even with limited data.

This study therefore proposes an integrated approach that combines SPC and BN in a four-phase cycle applied to the RN073 pocket tissue production machine at SITRACEL S.A., located in Central Africa. The two targeted performance indicators are Non-Production Time (NPT, target $\leq$ 2.07 min/h) and Breakdown Time (BDT, target $\leq$ 1.20 min/h), collected as hourly data over the periods of February, April, and May 2026. The objective of this study is twofold: first, to demonstrate the added value of Bayesian networks in diagnosing the root causes of production stoppages when coupled with SPC; and second, to quantitatively measure the impact of targeted interventions on maintenance KPIs in an African industrial context, a region virtually absent from the literature on Lean Six Sigma.

1. Materials and Methods

1.1. Statistical Process Control (SPC)

Statistical Process Control (SPC) is a methodology based on the use of statistical tools to monitor, analyze, and control variability in industrial processes in real time. Its founding principle, established by Walter A. Shewhart as early as the 1920s, is the distinction between two types of variability: common-cause variability, which is inherent and structural to the

process, and special-cause variability, which is produced by identifiable and correctable factors. As long as only common-cause variability is present, the process is said to be under statistical control; as soon as a special-cause factor intervenes, it goes out of control and requires investigation.

The central tool of SPC is the control chart. It plots the temporal evolution of a performance indicator against statistically calculated limits derived from the natural variability of the process. These limits are: the upper control limit (UCL) and the lower control limit (LCL). Any point that exceeds these limits, or any non-random pattern (trend, sinusoid, cluster), is an alarm signal. Woodall (2017) emphasizes that rigorous data collection and the use of reference data in Phase I constitute a fundamental prerequisite that is too often neglected, and that the role of modeling in statistical process monitoring remains an under-exploited lever between theory and industrial practice. In modern manufacturing environments, this dimension is becoming increasingly important. He and Wang (2018) position statistical process monitoring as a large-scale data analysis tool for smart manufacturing, proposing a roadmap of recent developments and identifying process-feature-based methods as the most promising for the next generation of industrial monitoring.

In this study, the two maintenance performance indicators tracked are continuous variables expressed in minutes per hour of production. These variables are Non-Production Time (NPT) and Breakdown Time (BDT). To implement SPC for monitoring these two KPIs, we used $\bar{X}$-R charts, which consist of two complementary charts: the $\bar{X}$ chart, which monitors the process average and detects shifts in position, and the R chart, which monitors the within-group range and detects variability instabilities. These two charts must work together: if the R chart is out of control, the limits calculated for the $\bar{X}$ chart can be inaccurate and lead to type I or II errors.

The control limits are calculated using the coefficients from the Shewhart table (A_2, D_3, D_4) depending on the subgroup size, according to the formulas shown in Table 1. This study was done using CL (control limit) values that were the company's targets for each KPI, along with the control limits from equations 2, 4, 5, and 6.

Table 1 : Formula for Upper and Lower control limite for Xbar and R charts

$UCL(\bar{X}) = \bar{\bar{X}} + A_2 * \bar{R}$ (1)	$UCL(\bar{X}) = CL + A_2 * \bar{R}$ (2)
$LCL(\bar{X}) = \bar{\bar{X}} - A_2 * \bar{R}$ (3)	$LCL(\bar{X}) = CL - A_2 * \bar{R}$ (4)
$UCL(R) = D_4 * \bar{R}$ (5)	$UCL(R) = D_4 * \bar{R}$ (5)
$LCL(R) = D_3 * \bar{R}$ (6)	$LCL(R) = D_3 * \bar{R}$ (6)

1.2. Bayesian Networks

Bayesian Networks (BN) are probabilistic graphical models that represent causal dependency relationships between random variables in the form of a Directed Acyclic Graph (DAG). They consist of parent nodes, intermediate nodes, and an output node. Mathematically speaking, BNs are defined as follows:

- A directed acyclic graph, G=(V,E), where V is the set of nodes of G and E is the set of arcs of G;
- A finite probability space (Ω,Z,P);

- A set of random variables associated with the nodes of the graph and defined on (Ω,Z,p), such that: $P(V_1, V_2, \ldots, V_n) = \prod_{i=1}^{n} P(V_i | C(V_i))$ **(7)**

With C(Vi) representing the set of causes (parents) of Vi in the graph G.

The most valuable characteristic of BNs in an industrial diagnostic context is their ability for bidirectional inference. A Bayesian Network can reason in two directions:

- Predictive direction (from causes to effects): Calculate the probability of an undesirable event based on the known state of the causes.
- Diagnostic direction (from effects to causes): starting from an observation at the output node, trace back to the most likely causes by redistributing probabilities across the parent nodes. It is this second direction that is
- exploited in this work.

Ademujimi et al. (2022) showed that Bayesian networks are a particularly suitable tool for fault diagnosis in smart manufacturing systems, especially for distinguishing parent nodes from ancestor nodes in the causal structure, which is exactly the goal of the sensitivity analysis conducted in this study. Wang et al. (2024) confirm that BNs allow for interpretable probabilistic reasoning under uncertainty, with the ability to identify root causes with explicit probabilities. This is a key quality in an industrial context where corrective decisions need to be justified and prioritized.

1.3. Method

The method used in this study combines SPC and Bayesian networks into a four-phase diagnostic sequence, embedded in the Lean Six Sigma DMAIC cycle. Pongboonchai-Empl et al. (2024), based on a systematic review of 692 articles, showed that the 'Analyze' phase of DMAIC is by far the best supported by advanced analytical tools, particularly machine learning and probabilistic methods. This confirms the structural need for more sophisticated diagnostic tools in industrial maintenance improvement projects. It is precisely in this phase that Bayesian networks strengthen the traditional approach.

The method implemented as follows:

Phase 1 - Primary SPC (Measurement / As-Is Assessment): This involves collecting NPT and BDT data hourly during the second half of February 2026. It then involves constructing $\bar{X}$ and R charts for both indicators. Next, the UCL and LCL limits are calculated. Finally, the process control status is assessed, and the gap relative to the company's operational targets (NPT ≤ 2.07 min/h; BDT ≤ 1.20 min/h) is quantified.

Phase 2 - BN Modelling (Analysis): it involves building the NPT and BDT causal graphs from the functional analysis of the RN073 machine. Then, initializing the CPTs (Conditional Probability Table) using February's data. After that, carrying out sensitivity analysis through successive scenarios on the output nodes. And finally, identifying the most discriminating nodes.

Phase 3 - Corrective Actions (Improve): it consists of targeting interventions on the root causes identified by the BNs, with priority allocation of maintenance resources according to the probabilistic hierarchy established.

Phase 4 - Secondary SPC (Control): it also involves collecting data but over the first half of April and then May 2026. Then comes monitoring the evolution of NPT and BDT averages compared to the initial state. And finally, the quantitative measurement of the impact of interventions and identifying residual second-order causes. The diagram in Appendix 1 gives a

structured representation of this closed-loop methodology for better long-term implementation. The strength of this method lies in its operational complementarity and its execution in a closed loop: SPC detects and quantifies, BN diagnoses and prioritises, Secondary SPC validates.

2. Results and Discussions

2.1. Presentation of the Industrial System

The industrial system examined in this case study is a production line for pocket tissues with a capacity of 100 packs per minute. It utilises Industry 2.0 technology and forms part of SITRACEL's fixed assets. SITRACEL S.A. is an industrial company operating in the textile sector, specifically in the processing of cellulose wadding for the manufacture of hygiene products, and is based in Central Africa, in Cameroon, in the cities of Douala and Yaoundé. This pocket tissue machine, known as the RN073, consists of four main units (B1, B2, B3 and B4) assembled in series to form the production line.

For better tracking of its equipment, the company has set up performance indicators for its maintenance system, including Non Production Time (NPT) or machine idle time and machine Breakdown Time (BDT). NPT should be less than or equal to 60 minutes per shift including the break (45 minutes), which is 2.07 minutes per hour of production, and BDT should be less than or equal to 2% of the time allotted to production during a shift, which is 1.20 minutes per hour. Maintenance data is analysed on a weekly basis. The tools used by the maintenance department for RCA (root cause analysis) are the Pareto chart, the 5 why's, and the fault tree. For this study, we combined SPC and BN with the company's tools to make tracking KPIs (NPT & BDT), diagnosing, and predicting the causes of production downtime easier and simpler.

2.2. The data collection system

The company has a maintenance data collection system that takes place at the end of each production shift. The pocket tissue machine is scheduled for production in two eight-hour shifts per day (the morning shift and the afternoon shift) from Monday to Saturday all year round. Each production shift gets a 45-minute break per day. To properly implement SPC and use daily maintenance data, we decided on an hourly data collection system. So we adjusted the maintenance data collection sheets for the pocket tissue machine to collect data at the end of each production hour for the NPT and BDT indicators.

For the evaluation of the current state, we collected data in the second half of February 2026, and to assess the impact of using BN for diagnosing and predicting production stoppage causes, we collected data during the first half of April and the first half of May.

2.3. Primary SPC: As-Is Situation

In this section, we looked at the current situation of the processes tracked by the NPT and BDT indicators through their daily monitoring during the second half of February and got the four curves in figures 1, 2, 3 and 4.

Non Production Time

The $\bar{X}$ chart in Figure 1 oscillates between 11 and 27 min/h, with the UCL set at 12.07 min. Approximately 83.3% of the points are above the upper control limit. The hourly average of 18.4 min/h for NPT over the February period exceeds the UCL by about 53%. This is not a one-off drift: it is a process operating structurally outside its control limits. The two visible troughs (23–24/02 and 26/02) do not represent a return to normal. They remain close to or on the UCL.

Figure 2 shows an oscillation range between 22 and 60 min, around a mean $\bar{R} \approx 44.83$ min, with a UCL of 74.12 min. No point exceeds the UCL, but the variability is large and persistent. The system is not explosively out of control; it is chronically unstable. The sinusoidal pattern of the chart suggests a cyclical assignable cause, potentially linked to a production cadence or shift rotation.

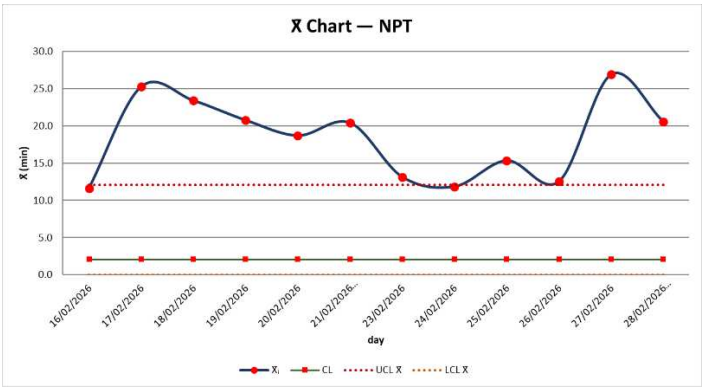


Figure 1: Xbar Chart – NPT – February

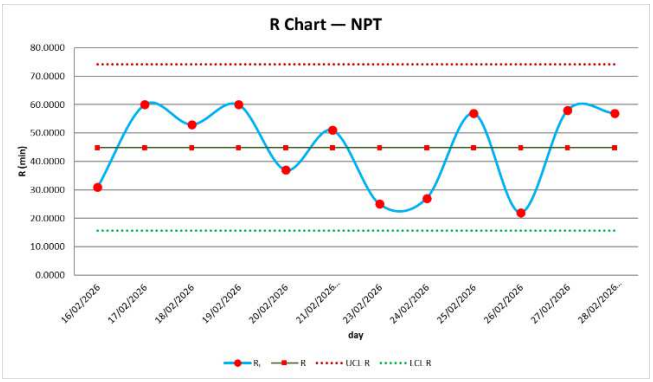


Figure 2 : R Chart – NPT – February

Machine Breakdown Time

The chart in Figure 3 shows oscillations between 7 and 21 min/h, with a UCL of 11.83 min and a CL of 2%. The majority of the points exceed the UCL, with two marked peaks (17–18/02 and 27–28/02) reaching 21 min. The troughs (23–24/02, 26/02) fall below the CL. This extreme amplitude reflects a bimodal instability: either the machine is running normally, or it is stopped for long periods. There are no stable intermediate zone. For Figure 4, the average Range is 47.17 min, with a UCL of 77.97 min. The chart reproduces exactly the same sinusoidal pattern as the NPT R Chart. Both indicators share the same variability dynamic, which confirms that they are driven by the same root causes. One point drops to around 20 min on 24/02, followed by an immediate rise back to around 60 min: no lasting stabilization.

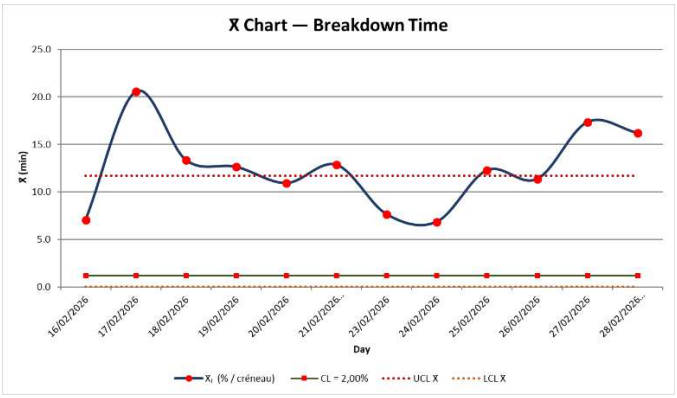


Figure 3 : Xbar Chart – Breakdown Time – February

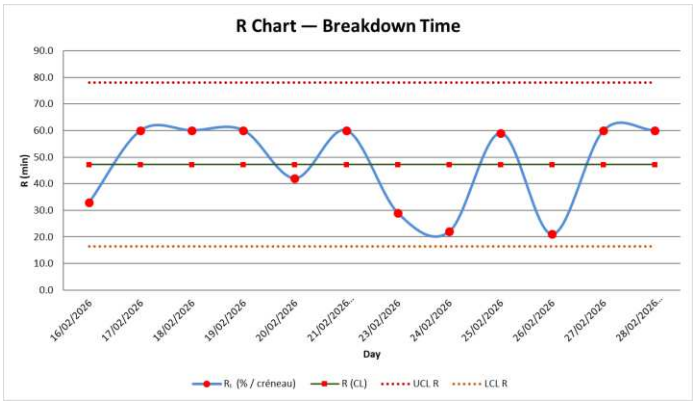


Figure 4 : R Chart – Breakdown Time – February

The four charts converge on an unambiguous diagnosis. The February process is out of statistical control on both critical indicators. The similarity of the sinusoidal patterns between NPT and BDT is not coincidental: it reveals an underlying common cause that has not yet been identified. We will analyze the causes of this gap using Bayesian networks by progressively tracing back the probability of each candidate cause for each indicator.

2.4.Bayesian Network Modelling

Before starting the diagnosis using Bayesian networks as a root cause analysis tool, we will first carry out the graphical and analytical modeling of our production system for each performance indicator.

Analytical and Graphical Modeling Using Bayesian Networks for NPT and BDT

Table 2 presents the candidate causes of machine production stoppages, classified by category.

Table 2 : NPT – Cause Assignment by Category

	Cause of downtime	Ref	Category	Description / Direct Cause
1	No load / No plan	A1	OP	Lack of production planning
2	No man power	A2	OP	Lack of available labour
3	Setting	A3	OP	Machine adjustment — operator task
4	Break down	A4	MA	Mechanical or electrical breakdown of the machine
5	Inspection	A5	MA	Checking the condition of the machine
6	Power cut	A6	EN	Power cut
7	Development	A7	OP	Training, testing and commissioning — planned activity
8	Tool change	A8	MA	Tooling replacement due to a change in product size
9	Process problem	A9	MT	Problem relating to the process or material
10	Machine maintenance	A10	MA	Planned preventive or corrective maintenance
11	Loading	A11	OP	Loading/supply — operator task
12	5S	A12	EV	Tidying and organising the workstation

OP (Operator), MA (Machine), MT (Material), EN (Energy), EV (Environment)

Table 3 shows how the pocket tissue machine is functionally structured based on its operating process for turning cellulose wadding into finished products.

Table 3: Functional structure of pocket tissue machine

Machine	Block Machine	Ref	STATION	Ref
RN-073 (M)	Production Unit of PT (B1)	DMO	Motorised wadding dispenser	C1
		SDG	Embossing station	C2
		SPC	Wadding folding and cutting station	C3
	10 PT Packaging Unit (B2)	SDT	Station for unloading and conveying packs of 10 PT to the packaging machine	C4
		SDP	Polyethylene unwinding and perforation station	C5
		SEP	Station for packaging, folding and longitudinal and lateral sealing of packs of 10 PT	C6
	10 PT Labelling Unit (B3)	SET	PT package labelling station	C7
	10x10 PT Bundling Unit (B4)	STE	Conveyor station for transporting packs of 10 PT to the bagging machine	C8
		SPP	Polypropylene unwinding station	C9
		SPS	Folding and longitudinal and lateral sealing station for 10x10 PT	C10

Figures 5 and 6 show the graphical representation of the NPT and BDT Bayesian networks according to potential causes. The analytical expressions of the NPT and BDT Bayesian networks are given by equations 9 and 10 respectively.

Bayesian Network NPT: G (V, E)

• **Nodes (V):** {A1, A2, A3, A4, A5, A6, A7, A8, A9, A10, A11, A12, OP, MA, EN, EV, MT, NPT} representing random variables.

• **Arcs (E)**: The directed arcs show direct dependencies.

• The **joint probability distribution** is factored as follows:

P(A1, …, A12, OP, MA, EN, EV, MT, NPT) = P(A1)*… * P(A12) * P(OP | A1, A2, A3, A7, A11) * P(EN | A6) * P(EV | A12) *P(MA | A4, A5, A8, A10) * P(MT | A9) * P(NPT | EN, OP, EV, MA, MT) (9)

Bayesian Network BDT: G (V, E)

• **Nodes (V):** {C1, C2, C3, C4, C5, C6, C7, C8, C9, C10, B1, B2, B3, B4, BDT} representing the random variables.

• **Arcs (E):** The directed arcs represent the direct dependencies.

• The **joint probability distribution** is factorised as follows:

P (C1, …, C10, B1, B2, B3, B4, BDT) = P(C1)*… * P(C10) * P(B1 | C1, C2, C3) * P(B2| C4, C5, C6) * P(B3 | C7) * P(B4 | C8, C9, C10) * P(BDT | B1, B2, B3, B4) (10)

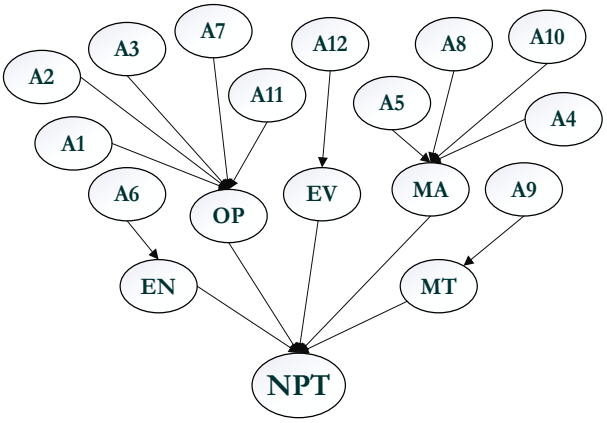


Figure 5 : Bayesian network modelling of NPT causes

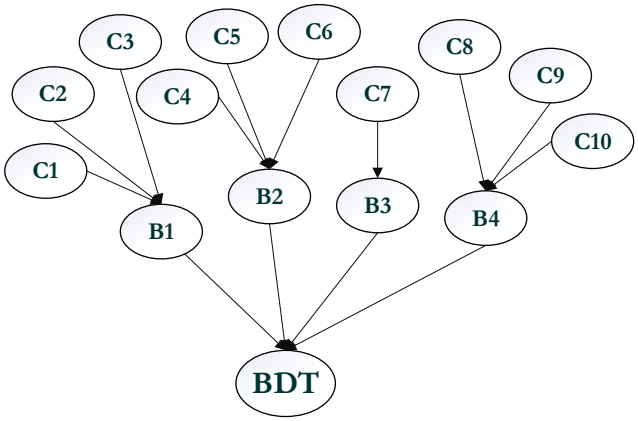


Figure 6 : Bayesian network modelling of BDT causes

Diagnosis and Forecasting of NPT and BDT Causes using Bayesian Networks

Following the graphical and analytical modelling of the NPT and BDT indicators using Bayesian networks, we carried out an implementation by incorporating the probabilities of non-occurrence for each potential cause and the availability rates of the machine stations set out in Table 4. These potential causes and the availability rates of the machine stations represent the parent nodes of the Bayesian networks. The primary data used to estimate the probabilities and availability rates were collected during the second half of February.

Table 4: Availability rates and probability of absence for potential causes

A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11
98.85%	99.12%	99.61%	80.00%	99.22%	99.72%	99.24%	99.11%	99.20%	98.32%	99.54%
C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**A12**
99.13%	98.67%	95.00%	99.14%	97.56%	97.65%	98.34%	98.82%	98.61%	97.08%	98.47%

Figures 7 and 8 show the NPT Bayesian network in Scenario 1 and Scenario 5 respectively. In Scenario 1, the run probability (72.6%) of the NPT output node has not yet been modified, but in Scenario 5, the probability of the output node has been set to 92.4%; we can therefore observe the changes in probabilities that have occurred across all other parent nodes and intermediate nodes in the Bayesian network.

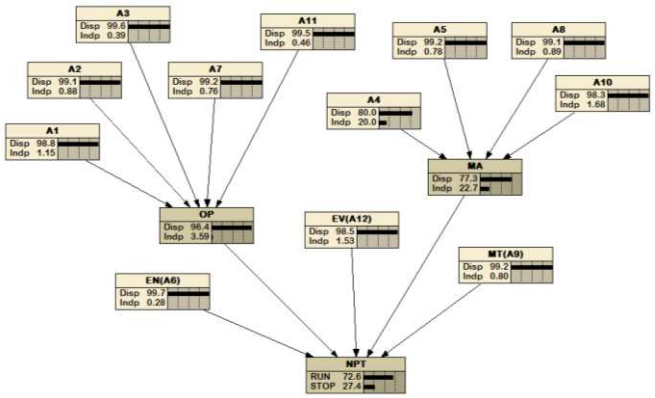


Figure 7: The NPT Bayesian network

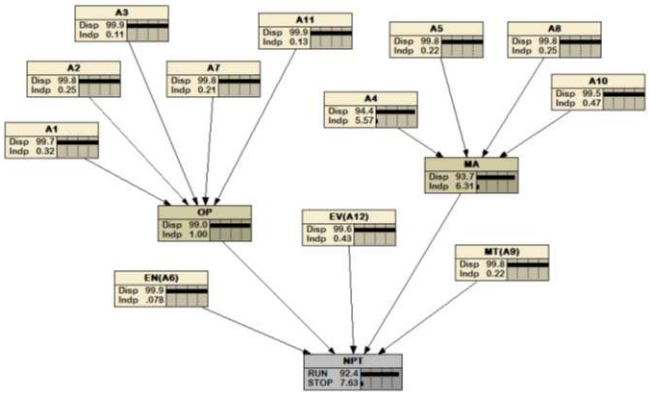


Figure 8: The NPT Bayesian network – Scenario 5

Table 5 shows the results of the sensitivity analysis obtained in each scenario based on the values assigned to the NPT output nodes. Scenario 7 is the real or existing case before changing the value of the output node.

Table 5: Sensitivity analysis of candidate causes for NPT

Node	Scenario1		Scenario 2		Scenario 3		Scenario 4		Scenario 5		Scenario 6		Scenario 7	
	Disp	Indp	Disp	Indp	Disp	Indp	Disp	Indp	Disp	Indp	Disp	Indp	Disp	Indp
A1	96.2	3.77	96.7	3.34	97.2	2.77	99.9	0.08	99.7	0.32	97.9	2.13	98.8	1.15
A2	97.1	2.89	97.4	2.56	97.9	2.12	99.9	0.061	99.8	0.25	98.4	1.63	99.1	0.88
A3	98.7	1.28	98.9	1.13	99.1	0.94	100	0.027	99.9	0.11	99.3	0.72	99.6	0.39
A4	34.4	65.6	41.8	58.2	51.8	48.2	98.6	1.39	94.4	5.57	63	37	80	20
A5	97.4	2.56	97.7	2.27	98.1	1.88	99.9	0.054	99.8	0.22	98.6	1.44	99.2	0.78
EN(A6)	99.1	0.92	99.2	0.81	99.3	0.68	100	0.02	99.9	0.078	99.5	0.52	99.7	0.28
A7	97.5	2.49	97.8	2.21	98.2	1.83	99.9	0.053	99.8	0.21	98.6	1.41	99.2	0.76
A8	97.1	2.92	97.4	2.59	97.9	2.15	99.9	0.062	99.8	0.25	98.4	1.65	99.1	0.89
MT(A9)	97.4	2.62	97.7	2.33	98.1	1.93	99.9	0.056	99.8	0.22	98.5	1.48	99.2	0.8
A10	94.5	5.51	95.1	4.89	95.9	4.05	99.9	0.12	99.5	0.47	96.9	3.11	98.3	1.68
A11	98.5	1.51	98.7	1.34	98.9	1.11	100	0.032	99.9	0.13	99.1	0.85	99.5	0.46
EV(A12)	95	5.02	95.5	4.45	96.3	3.69	99.9	0.11	99.6	0.43	97.2	2.83	98.5	1.53
OP	88.2	11.8	89.6	10.4	91.3	8.65	99.7	0.25	99	1	93.4	6.64	96.4	3.59
MA	25.7	74.3	34.1	65.9	45.4	54.6	98.4	1.58	93.7	6.31	58.1	41.9	77.3	22.7
NPT - RUN	10.3	—	20.4	—	34	—	98.1	—	92.4	—	49.4	—	72.6	—
NPT - STOP	89.7	—	79.6	—	66	—	1.91	—	7.63	—	50.6	—	27.4	—

The RUN probability of the NPT output node varies from 10.3% (scenario 1) to 98.1% (scenario 4). Following this variation, we observe that node A4 (machine Breakdown) is the most discriminating: its availability rate goes from 34.4% to 98.6%, with uncertainty (Indp) completely reversing from 65.6% to 1.39%. Node MA (intermediate) follows the same logic: very low (25.7%) in scenario 1, almost certain (98.4%) in scenario 4.

Figures 9 and 10 present the BDT Bayesian network in the real case scenario 1 and in scenario 2 where the RUN probability of the output node is set to 92.2%. From scenario one to scenario two, we observe a variation in the probabilities of the two parents and the intermediate nodes.

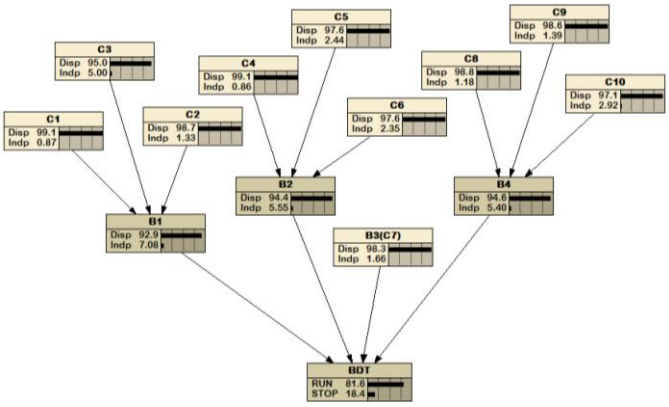


Figure 9: BDT Bayesian network

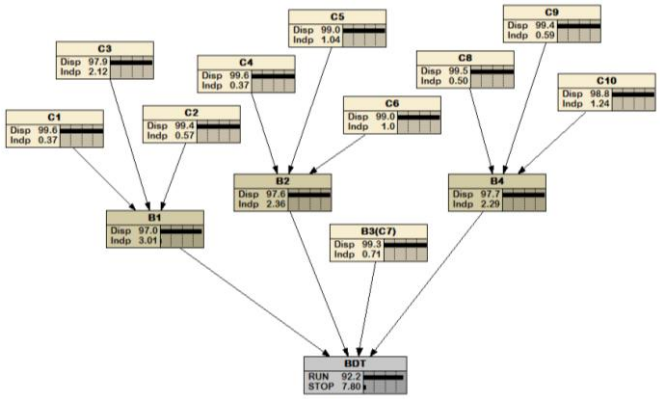


Figure 10: BDT Bayesian Network – Scenario 2

Table 6 presents the scenarios generated by varying the RUN probability value of the BDT Bayesian network from 7.95% to 98.0%. Upon examining the simulation results, we observe that node C3 (Wadding folding and cutting station) is the most sensitive: its availability varies from 99.4% to 74.9%, with uncertainty (Indp) rising from 0.55% to 25.1%. This is the most discriminating node in the network. Nodes B1 and B2 (intermediate nodes) follow the same downward trend, with B1 falling from 99.2% to 64.5%, reflecting the cumulative deterioration of inputs C1, C2 and C3.

Table 6: Sensitivity analysis of the machine's stations

Node	Scenario 1		Scenario 2		Scenario 3		Scenario 4		Scenario 5		Scenario 6		Scenario 7	
	Disp	Indp	Disp	Indp	Disp	Indp	Disp	Indp	Disp	Indp	Disp	Indp	Disp	Indp
C1	99.1	0.87	99.6	0.37	99.9	0.096	98.3	1.72	97.8	2.24	96.2	3.8	95.6	4.36
C2	98.7	1.33	99.4	0.57	99.9	0.15	97.4	2.63	96.6	3.43	94.2	5.81	93.3	6.67
C3	95	5	97.9	2.12	99.4	0.55	90.1	9.9	87.1	12.9	78.2	21.8	74.9	25.1
C4	99.1	0.86	99.6	0.37	99.9	0.095	98.3	1.7	97.8	2.22	96.2	3.75	95.7	4.31
C5	97.6	2.44	99	1.04	99.7	0.27	95.2	4.83	93.7	6.29	89.3	10.7	87.8	12.2
C6	97.6	2.35	99	1	99.7	0.26	95.3	4.65	93.9	6.06	89.7	10.3	88.2	11.8
C8	98.8	1.18	99.5	0.5	99.9	0.13	97.7	2.34	97	3.04	94.8	5.15	94.1	5.92
C9	98.6	1.39	99.4	0.59	99.9	0.15	97.2	2.75	96.4	3.58	93.9	6.07	93	6.97
C10	97.1	2.92	98.8	1.24	99.7	0.32	94.2	5.78	92.5	7.53	87.3	12.7	85.4	14.6
B1	92.9	7.08	97	3.01	99.2	0.78	86	14	81.7	18.3	69.1	30.9	64.5	35.5
B2	94.4	5.55	97.6	2.36	99.4	0.62	89	11	85.7	14.3	75.8	24.2	72.2	27.8
B3(C7)	98.3	1.66	99.3	0.71	99.8	0.18	96.7	3.29	95.7	4.28	92.8	7.25	91.7	8.33
B4	94.6	5.4	97.7	2.29	99.4	0.6	89.3	10.7	86.1	13.9	76.4	23.6	72.9	27.1
BDT -RUN	81.6	—	92.2	—	98	—	63.7	—	52.7	—	19.9	—	7.95	—
BDT -STOP	18.4	—	7.8	—	2.03	—	36.3	—	47.3	—	80.1	—	92.1	—

2.5. Secondary SPC : Situation after

This section is all about the post-intervention validation phase. After the Bayesian network diagnosis identified A4 (Machine Breakdown) as the main cause of NPT and C3 (Folding and Cutting Station) as the most crucial node of BDT, the data from April and May 2026 allow us to see the real impact of the corrective actions on the two critical maintenance indicators.

Figures 11 and 12 show a 57% drop in the average NPT from February (18.4 min/h) to April (7.93 min/h), followed by a further improvement in May (-4.5% on April). The process goes significantly below the old UCL of 12.07 min/h. However, the operational target of 2.07 min/h is still far off: the remaining gap is still about 5.5 min/h in May. The downward trend is real and gradual, but not enough to confirm full control of the process.

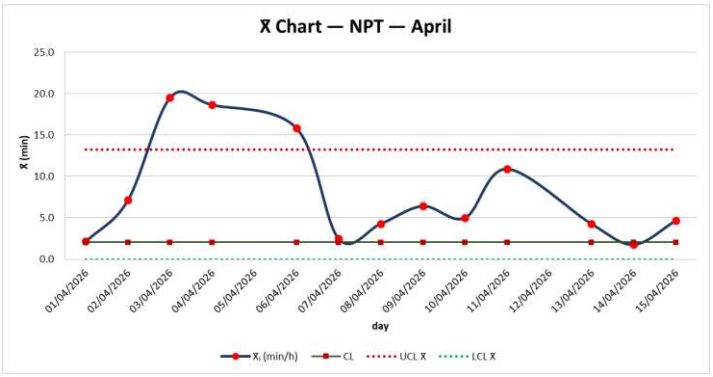


Figure 11 : Xbar chart – NPT – April

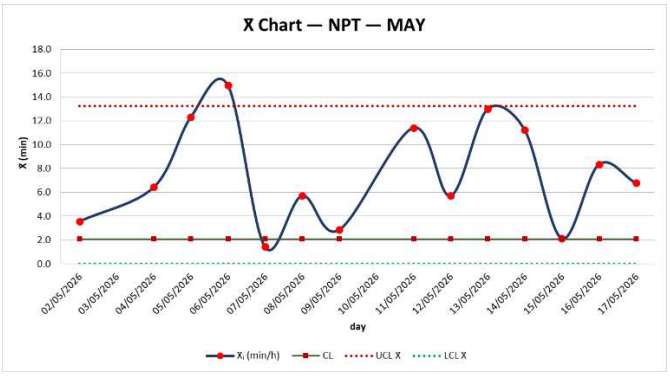


Figure 12 : Xbar chart – NPT – May

The BDT shows the most encouraging trend. Figure 13 shows a drop of 41.7% in one month, from 12.43 to 7.25 min/h; figure 14 confirms a speeding up of the trend in May (an extra −29.7%). This result fits with the Bayesian diagnosis: the targeted treatment of C3 (Folding and cutting station) has a direct and measurable effect on the BDT. Despite this, the target of 1.20 min/h is still ahead, with a remaining gap of ~4 min/h in May.

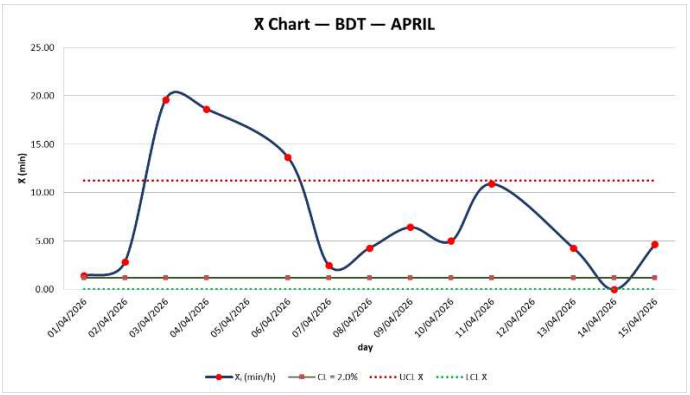


Figure 13 : Xbar chart – BDT – April

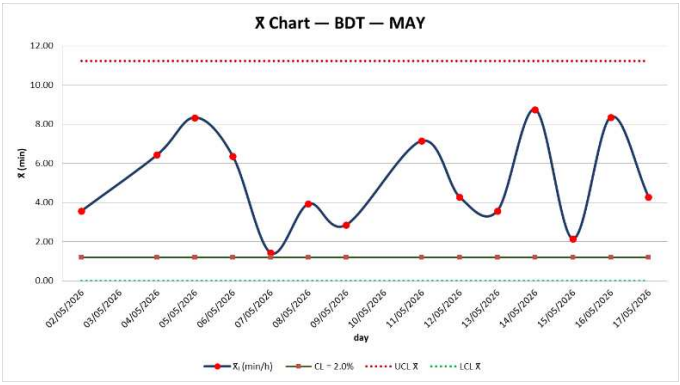


Figure 14 : Xbar chart – BDT – May

2.6. Analysis of the Impact of BNs on NPT and BDT

This section is about looking at the impact of using Bayesian networks as a tool for root cause analysis for KPIs tracked by SPC. Table 7 sums up the whole process in four columns. It compares the initial out-of-control state (February), the two post-intervention cycles (April, May) and the operational thresholds set by the company.

*Table 7: The mean values for the NPT and BDT KPIs and the company's targets**

KPI	February	April	May	Target
NPT (min/h)	18.4	7.93	7.57	2.07
BDT (min/h)	12.43	7.25	5.10	1.20

For the NPT KPI, the total reduction between February and May reaches −58.9%. For BDT, it reaches −59%. The two indicators almost mirror each other, which isn't a coincidence since the Bayesian diagnosis had already established in section 2.3 that NPT and BDT share the same root causes (A4 – Machine Breakdown, and the degradation of C3). The co-evolution we see here retrospectively validates the modeling. However, both indicators are still far from their targets: 72.6% of the initial gap remains to be filled for NPT and 73.2% for BDT.

Between April and May, the NPT only drops by 0.36 min/h (−4.5%), compared to a drop of 10.47 min/h between February and April. The BDT, on the other hand, continues to decline more sharply: −2.15 min/h between April and May (−29.7%). This divergence suggests that for the NPT, the easy gains have already been captured. The remaining causes (A1 – planning, A10 – preventive maintenance, OP – operator factor) now carry a relatively heavier weight and will be harder to reduce without targeted organizational actions. For the BDT, the momentum is still active. The handling of C3 (Folding and Cutting Station) is still having an effect in May, which suggests that the corrective actions on this equipment are still in the consolidation phase.

The contribution of Bayesian networks is clear and measurable here: the probabilistic ranking of causes made it possible to target interventions precisely, avoiding the scatter of effort typical of a Pareto-only approach. However, reaching the targets will require a second cycle of Bayesian modeling, using data from April-May to recalibrate the probabilities for residual causes and identify the nodes that are now dominant in the updated network.

2.7. Discussions

SPC–BN Complementarity

The main methodological contribution of this work lies in the articulation between $\bar{X}$-R control charts and Bayesian networks for the diagnosis of production stoppages. This combination is not intuitive: Control charts effectively detect out-of-control conditions, but they are not designed to identify the causes. Alaeddini A. and Dogan I. (2011) explicitly established this fact: despite their robustness in detecting out-of-control conditions, control charts remain limited tools for failure diagnosis. In response to this limitation, they developed a network capable of capturing cause-and-effect relationships between chart patterns, process information, and potential assignable causes, trained within a Bayesian network framework to enable real-time identification of single and multiple failure causes.

Our study fits directly into this approach: the Primary SPC (February) served as the detection phase, and Bayesian networks took over for the diagnostic phase, producing a probabilistic ranking of causes. This sequence detection → diagnosis → action → verification (Secondary SPC) is itself a structural contribution, rarely formalized in African industrial contexts.

Cobb and Li (2019) also showed that BNs are especially useful when sample sizes are small and managers are trying to detect slight changes in defect rates. The BN model outperformed adaptive np charts in most experimental scenarios. This result highlights the relevance of the methodological choice here: the data collected at the end of each production day are naturally small subgroups, which strengthens the comparative advantage of the Bayesian approach over just doing a Pareto analysis.

Bayesian network modeling and node sensitivity

The sensitivity analysis carried out on the two networks (NPT and BDT) produced results consistent with those found in recent literature on Bayesian root cause analysis in the manufacturing sector. Wang K. et al (2024) proposed a Bayesian ensemble network for analysing the root causes of product defects based on historical production data, demonstrating that Bayesian networks (BNs) enable interpretable probabilistic reasoning under uncertainty; with the ability to identify root causes with explicit probabilities and to predict quality risks in production.

In our case, node A4 (Machine Breakdown) turned out to be the most telling on the NPT network, with an availability rate ranging from 34.4% to 98.6% depending on the scenario, and uncertainty that completely reverses. On the BDT network, node C3 (Folding and Cutting

Station) shows the same behavior, with availability varying from 74.9% to 99.4%. These results are consistent with the logic of Bayesian modeling: the nodes whose marginal probability changes the most in response to changes in the output node are the ones that have the dominant causal influence on the monitored indicator. This ability to identify the simple or multiple causes of failures in real time, while gradually improving performance through error learning, is one of the main advantages of Bayesian networks applied to SPC.

The measured impact of interventions

The Secondary SPC data show a reduction of about 59% on both indicators between February and May. This level of performance is in line with results documented in the literature on Lean Six Sigma and maintenance integration. In the textile sector, using LSS tools has led to productivity increases of around 17.8%, efficiency improvements of 12.46%, reductions in defect rates (for example, from 12.7% to 6.71% in cutting processes) and lead time reductions of up to 80% (Yeasir A. et al, 2026). The reduction achieved here in BDT (from 12.43 to 5.10 min/h) is of a comparable magnitude, although the absolute targets (1.20 min/h) are still out of reach at this stage.

The residual gap observed is 7.57 min/h for NPT with a target of 2.07, and 5.10 min/h for BDT with a target of 1.20, which doesn't invalidate the approach. This shows that the main causes (A4, C3) were correctly addressed, but secondary causes (A10 – preventive maintenance, A1 – planning, C5/C6 – packaging stations) now have a relatively bigger impact on the remaining variability. This shift in the dominant cause after an initial targeted intervention is typical in complex industrial processes and justifies setting up a second cycle of Bayesian modeling based on post-intervention data.

Study positioning and limitations

The residual gap observed is 7.57 min/h for NPT with a target of 2.07, and 5.10 min/h for BDT with a target of 1.20, which doesn't invalidate the approach. This shows that the main causes (A4, C3) were correctly addressed, but secondary causes (A10 – preventive maintenance, A1 – planning, C5/C6 – packaging stations) now have a relatively bigger impact on the remaining variability. This shift in the dominant cause after an initial targeted intervention is typical in complex industrial processes and justifies setting up a second cycle of Bayesian modeling based on post-intervention data.

However, several limitations must be noted. Firstly, the initial probabilities fed into the Bayesian networks are derived from data for February, a period clearly outside the control phase, which may introduce a bias in the estimation of parent nodes. A third round of BN calibration, using data from April–May, would help to correct this bias and refine the prediction of residual causes. Secondly, the current network modeling does not yet take into account the temporal dependencies between successive failures. This limitation could be overcome in a future version of the model using dynamic Bayesian networks (DBNs).

Conclusion

This study demonstrated the operational relevance of an integrated SPC–BN approach applied to the management of production stoppages in an African industrial context. By combining the statistical detection of deviations via $\bar{X}$-R charts with the diagnostic capabilities of Bayesian networks, it was possible not only to quantify the gap between actual performance and operational targets (NPT $\leq$ 2.07 min/h; BDT $\leq$ 1.20 min/h), but above all to accurately identify

the priority root causes: node A4 (Machine Breakdown) for NPT and node C3 (Bending and Cutting Station) for BDT.

The results of the Secondary SPC confirm the effectiveness of the targeted interventions: a reduction of approximately 59 per cent was recorded for both indicators between February and May 2026. These results are consistent with the gains documented in the literature on the application of LSS tools in manufacturing environments (Yeasir et al., 2026). However, the absolute targets have yet to be met, indicating that secondary causes such as preventive maintenance (A10), planning (A1) and packaging stations (C5, C6) now account for an increasing relative proportion of the residual variability. This phenomenon of a shift in the dominant cause is inherent in complex industrial processes and supports the establishment of a continuous improvement loop, as set out in the methodology.

With this in mind, the way forward is clear: to recalibrate the Bayesian networks using data from April–May in order to update the conditional probabilities, and then to undertake a second cycle focusing on the residual causes identified. Ultimately, the integration of dynamic Bayesian networks (DBNs) would enable the modelling of temporal dependencies between successive failures, thereby overcoming one of the model's current limitations. Furthermore, the contribution of this study extends beyond the purely technical framework: it enriches a field of LSS literature still largely dominated by Asian contexts by documenting a rigorous approach applied to a real-world facility in Cameroon, thereby responding to the call by Fatemeh et al. (2025) to broaden the geographical representativeness of studies on sustainable continuous improvement.

Reference

[1] Ademujimi, T. & Prabhu, V. (2022). Digital twin for training Bayesian networks for fault diagnostics of manufacturing systems. *Sensors*, 22(4), 1430. https://doi.org/10.3390/s22041430

[2] Alaeddini, A. & Dogan, I. (2011). Using Bayesian networks for root cause analysis in statistical process control. *Expert Systems with Applications*, 38(9), 11230–11243. https://doi.org/10.1016/j.eswa.2011.02.171

[3] Cobb, B. & Li, L. (2019). Bayesian networks for statistical process control with attribute data. *International Journal of Quality & Reliability Management*, 36(2), 232–256. https://doi.org/10.1108/IJQRM-10-2017-0227

[4] Fatemeh, G., Matthew, J. F. & Benjamin, G. (2025). Green lean six sigma for sustainable development: a systematic review of evolution, challenges, and future pathways. *Clean Technologies and Environmental Policy*, 27, 9239–9262. https://doi.org/10.1007/s10098-025-03281-y

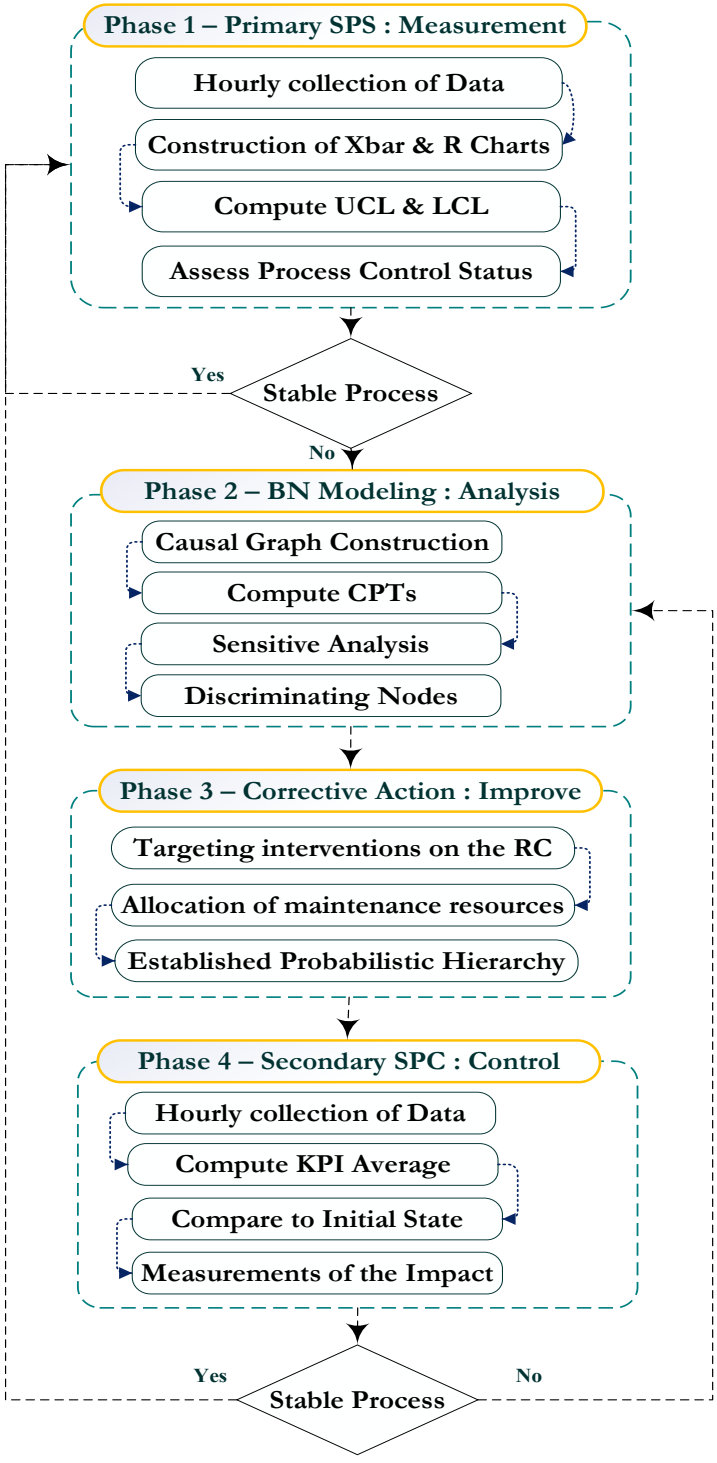
[5] He, Q. P. & Wang, J. (2018). Statistical process monitoring as a big data analytics tool for smart manufacturing. *Journal of Process Control*, 67, 35–43. https://doi.org/10.1016/j.jprocont.2017.06.012

[6] Pongboonchai-Empl, T., Antony, J., Garza-Reyes, J. A., Komkowski, T. & Tortorella, G. L. (2024). Integration of Industry 4.0 technologies into Lean Six Sigma DMAIC: a systematic review. *Production Planning & Control*, 35(12), 1403–1428. https://doi.org/10.1080/09537287.2023.2188496

[7] Wang, K., Liu, C. & Lu, Y. (2024). Ensemble Bayesian Network for root cause analysis of product defects via learning from historical production data. *Journal of Manufacturing Systems*, 75, 102–115. https://doi.org/10.1016/j.jmsy.2024.06.001

[8] Woodall, W. H. (2017). Bridging the gap between theory and practice in basic statistical process monitoring. *Quality Engineering*, 29(1), 2–15. https://doi.org/10.1080/08982112.2016.1210449

[9] Yeasir, A., Anik, D., Mohammed, A. A. & Rony Mia. (2026). Applications of lean manufacturing in the textile garments industry. *The International Journal of Advanced Manufacturing Technology*, 143, 4735–4774. https://doi.org/10.1007/s00170-026-17713-6

Appendix

Appendix 1 : Methodology diagram