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Predictive Surface Defect Detection in Particleboard Manufacturing using Defect Tracking Matrix–Principal Component Analysis Framework toward Zero Defect Manufacturing

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Abstract: Zero Defects Manufacturing (ZDM) is a proactive quality strategy aimed at preventing defects during production. This study proposes a novel integrated method using the Defect Tracking Matrix (DTM) and Principal Component Analysis (PCA) to predict the sources of surface defects in particleboard manufacturing. The authors evaluated twenty technical attributes and sixteen quality defects. Results showed that duct cleaning, setting the blower, screen cleaning, press calibration, and blade sharpening were key contributors to detecting patterns. The DTM-PCA framework improves traceability and helps implement ZDM through structured, data-driven analysis in a previously unexplored context.

Keywords: Defect Tracking Matrix (DTM); Particleboard Industry; Prediction; Principal Component Analysis (PCA); Quality Control; Zero Defects Manufacturing (ZDM)

1. Introduction

In an era of globalized markets and technological transformation, product quality has emerged as a critical determinant of industrial competitiveness, sustainability, and customer retention. With rising consumer expectations and regulatory standards, manufacturing firms must consistently deliver high-quality outputs to ensure operational resilience and long-term viability. In response, organizations increasingly invest in systematic quality enhancement initiatives[1]. Accordingly, quality management remains a central focus of industrial research, with emerging frameworks such as Quality 2030 offering future-oriented strategies to achieve performance excellence across value chains[2]. Numerous studies have developed methodologies for quality enhancement by leveraging emerging technologies. The competitiveness of the manufacturing industry tends to decline in the absence of technological adoption. Technological advancements brought by the Industry 4.0 era have significantly transformed the manufacturing sector[3]. In this context, the concept of Zero Defect Manufacturing (ZDM) has emerged as a new paradigm in quality improvement, utilizing technology through four strategic approaches: detection, prediction, prevention, and repair[4]. The implementation of the ZDM method is expected to enhance sustainability, competitiveness, efficiency, and profitability for manufacturing enterprises [5]. Among the four strategic pillars of ZDM, predictive analysis has become one of the key approaches[6]. Predictive strategies represent a progression beyond traditional detection methods, increasingly leveraging artificial intelligence (AI). Several studies have explored detection and prediction frameworks, including those focused on human monitoring environments[7], prediction of material properties using machine learning[8], flexural strength estimation via artificial neural networks[9], and crop yield forecasting in agriculture[8]. These examples reflect the expanding role of predictive methods in driving quality improvements. In addition, AI-based approaches are also being used to promote sustainability in the manufacturing sector[9].

In this sector, product quality is essential not only to meet consumer expectations but also to maintain competitiveness in both domestic and international markets. The wood manufacturing industry—particularly particleboard production—plays a critical role in maximizing the utilization of wood resources, reducing waste, and minimizing reliance on virgin forest materials[10]. Quality control challenges remain significant, particularly in ensuring that final products meet stringent standards for strength, durability, and surface quality. Public awareness of environmental preservation has also increased, especially in developed countries, where concerns over their environmental impact have increasingly influenced the consumption of wood-based products. Europe remains a significant hub for particleboard production, with Germany, Poland, Italy, Austria, and France among the leading countries in this field. Asia, however, has become the largest producer, followed by Europe, the Americas, Africa, and Oceania[11]. According to the Particle Board Industry Research Report in China, as of June 30, 2023, a total of 327 production lines were in operation, with a combined capacity of 45.72 million m³/year, projected to reach 65 million m³/year by the end of 2024[11]. While prior studies have investigated defect detection in wooden components, opportunities remain for methodological enhancement—such as collecting cross-manufacturer defect data, implementing more granular defect segmentation, and increasing the scale of datasets for training predictive models[12]. Common types of observed surface defects include big shavings, sand leakage, glue spots, soft patches, and oil contamination [13]. The global trend indicates a rising demand for particleboard products, with Indonesia recognized as one of the world's largest wood-producing nations [14]. According to national statistics, particleboard production in Indonesia has also experienced consistent growth, reflecting both domestic demand and export orientation, as shown in Table 1.

However, existing quality control methods in this industry often rely on reactive inspection and manual evaluation, which may limit real-time corrective capability. To address these limitations, recent studies have proposed advanced defect detection models for wood-based materials using image reconstruction and deep learning approaches[15]. In parallel, other researchers have developed lightweight, edge-deployable neural network architectures aimed at enabling fast and scalable defect identification in panel production environments[16]. These developments underscore the pressing need for structured and predictive frameworks that integrate traceable defect mapping with interpretable statistical modeling.

Table 1: Production of particleboard in Indonesia

Wood Type	Unit	2020	2021	2022	2023
Chip and Particle	m^3 (million)	21.54	29.22	39.7	42.20
Particle board	m^3 (thousands)	17.65	26.04	166.65	202.64

With the increasing demand for particleboard products, rigorous and timely quality inspection becomes essential to ensure that only defect-free products reach the market[17]. As a proactive quality framework, Zero Defect Manufacturing (ZDM) offers a systematic approach to prevent defects before they propagate along the production chain[18]. Among the key requirements of ZDM is not only detecting defects but also accurately identifying their root causes[19]. Traditional methods of defect tracing often rely on manual inspection or post-hoc diagnosis, which may lead to delays and inconsistencies[20]. In contrast, emerging technologies developed under the Industry 4.0 paradigm offer new opportunities for real-time and data-driven quality control. Therefore, there is an urgent need to develop structured, efficient, and predictive methods that can trace defect origins with greater precision. This study addresses that need by introducing a hybrid methodology that combines the Defect Tracking Matrix (DTM) for structural mapping and Principal Component Analysis (PCA) for dimensional simplification and prioritization of root causes[21].

Therefore, the development of effective and integrated quality control strategies is crucial for achieving the goals of Zero Defect Manufacturing (ZDM) in the wood-based industry. Among the key challenges in particleboard production is the identification of surface defects, which often elude traditional inspection techniques[11]. The success of predictive quality systems heavily depends on the ability to trace defect origins with precision [19]. One promising method in this domain is the Defect Tracking Matrix (DTM), which systematically connects technical processes with quality defect types through a relational matrix[20]. Initially designed for Mass Customization Production (MCP) systems, DTM offers transparency in tracing defects, but becomes increasingly complex as the number of quality defects (QD) entries grows. This often leads to inefficiency and cognitive overload when applied to large-scale industrial systems. To address this limitation, this study integrates Principal Component Analysis (PCA) as a dimensionality reduction technique that simplifies the DTM structure without sacrificing critical information[19]. The resulting DTM–PCA framework enables rapid defect traceability, improved prioritization of technical attributes, and enhanced predictive capabilities.

This paper presents the application of the DTM–PCA framework in the context of particleboard manufacturing, specifically at PT Kutai Timber Indonesia (PT KTI). The remainder of this article is organized as follows: Section 2 outlines the methodology, including DTM construction and PCA implementation; Section 3 describes the case study and results; Section 4 provides a detailed discussion; and Section 5 concludes with insights and future directions. The contributions of this study are as follows:

- It introduces a hybrid integration of the Defect

Tracking Matrix (DTM) and Principal Component Analysis (PCA) for predictive surface defect detection in particleboard manufacturing.

- It reduces the dimensional complexity of traditional DTM by identifying dominant technical attributes through PCA, while maintaining interpretability.
- It applies the approach in a real-world industrial context with structured expert-driven data, addressing challenges in transparency and traceability.
- It offers a simplified yet systematic tool for operational decision-making, contrasting with prior studies that often rely on image-based or algorithmic black-box models.

2. Methodology

2.1. Detection Strategy in ZDM

The concept of Zero Defect Manufacturing (ZDM) was first introduced in 1965 by the U.S. Army Perishing Missile System as a quality initiative designed to eliminate errors in mission-critical components. Over time, ZDM evolved into a comprehensive quality strategy that integrates proactive control mechanisms to minimize and ideally eliminate defects throughout the production process[22]. In the context of Industry 4.0, ZDM has become an essential paradigm that unifies digital manufacturing, smart monitoring, and advanced analytics to achieve zero-defect goals in real-time environments.[23.]

ZDM typically structures itself around four interdependent strategic pillars: detection, prediction, prevention, and repair, as illustrated in Figure 1.

The detection strategy focuses on early identification of anomalies before they propagate along the production chain. The detection strategy focuses on identifying quality issues as early as possible in the production chain. Upon detecting a defect, the prediction strategy anticipates its recurrence and potential spread to later process stages. It relies on continuous quality inspection, sensor-based monitoring, and human–machine interface feedback. Prediction builds upon detection, aiming to anticipate

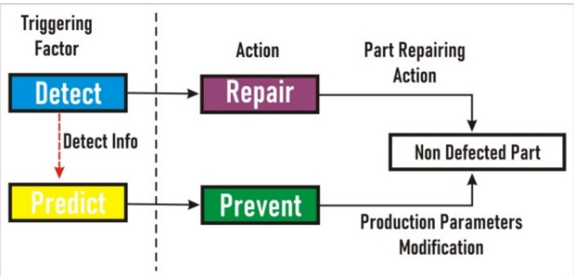

Fig. 1: Element of ZDM[22)]

defect recurrence using analytical or AI-based models. Prevention attempts to eliminate the root causes before defects manifest, while repair addresses unavoidable defects via rework or remanufacturing[24)]. Detection plays a pivotal role in ensuring the success of the other ZDM strategies. According to Psarommatis et al.,[22)], the ability to recognize abnormal patterns early enables the deployment of prevention and repair actions with minimal production disruption. In modern implementations, time data acquisition and machine learning-based fault classifiers, especially in high-volume or customized manufacturing settings[27)],.increasingly supported detection systems. The Defect Tracking Matrix (DTM) method is an excellent approach for monitoring faults and identifying their causes, as demonstrated in prior studies[25)]. Grobler-Dębska et al.[26)] emphasize that effective detection is also vital for dynamic scheduling and reconfiguration, especially in automated environments. Their algebraic-logical ZDM scheduling framework illustrates that detection data must be systematically linked to response mechanisms, which in turn enable closed-loop quality control. Furthermore, Lin and Chen[24)] propose a hybrid Decision Support System (DSS) that integrates detection with predictive optimization using computational intelligence, showcasing how detection quality influences the reliability of predictive decisions.

In this study, detection is positioned as the first critical layer of quality assurance, enabling the identification of defects in surface characteristics—such as sanding inconsistencies, press calibration errors, and dust-related flaws—that are prevalent in particleboard manufacturing. However, to ensure timely correction and sustainable improvement, detection must be coupled with robust defect tracking and predictive frameworks. One such method is the Defect Tracking Matrix (DTM), which provides traceability between technical operations and observed quality outcomes. DTM serves as a foundation for defect diagnosis and prevention, and its integration with Principal Component Analysis (PCA) will be discussed in subsequent sections.

2.2. Procedure of DTM for prediction

The Defect Tracking Matrix (DTM) is a systematic quality tool that connects technical attributes (TAs) from production processes with observed quality defects (QDs). Originally derived from the House of Quality (HoQ) framework, DTM offers a matrix-based approach to assess how each technical action contributes to different defect types in complex manufacturing environments[27)]. In this study, the DTM was constructed to support predictive quality strategies by organizing the relationships between TAs and QDs across four critical process stages: forming, hot pressing, cutting, and sanding. Each sub-process generated an individual DTM, which was subsequently combined into a modular DTM chain, enabling full

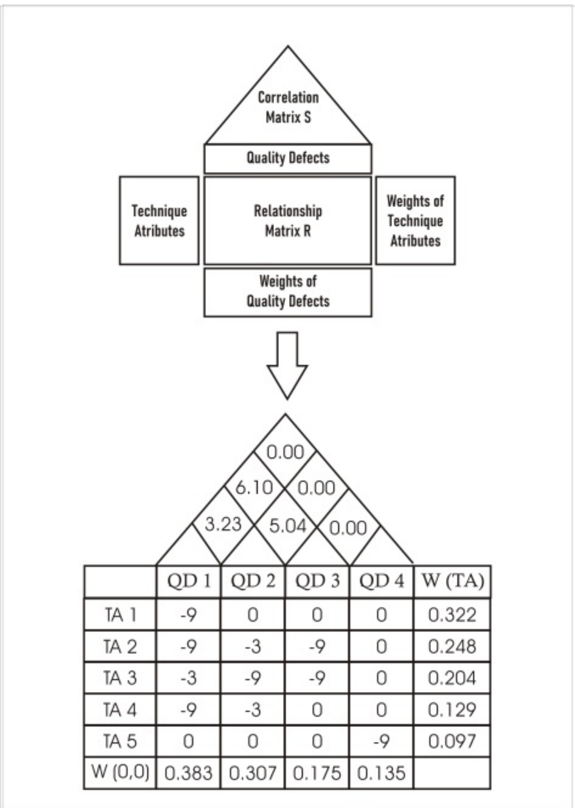

Fig. 2: Model of the DTM

traceability throughout the production line. Figure 2 shows an example of the DTM model. The procedures for constructing a DTM are as follows[21]:

Step 1: Identify Technical Attributes (TAs)

The first step involves identifying the technical attributes (TAs) that characterize each modular process in particleboard manufacturing. As proposed by Wang et al. (2007;2013), each TA represents a specific process operation, parameter setting, or condition that may influence product quality. TAs are denoted as TA_1 to TA_m, and each is assigned a corresponding weight $w(TA_i)$ based on its manufacturing complexity and cost contribution. In the context of this study, TAs were selected through field observation and expert input, focusing on process activities that are operationally controllable and have a direct relationship with surface defect occurrence. Examples include blower settings, duct cleaning frequency, glue spray rate, and press calibration accuracy. This structured approach ensures that the selected attributes not only reflect practical industrial relevance but also align with the methodological foundation of DTM modeling.

Step 2: Identify Quality Defects (QDs)

Next, quality defects (QDs) that occur during production are listed and categorized. These may include surface anomalies, material inconsistencies, or dimensional errors. Each QD is assigned a severity-based weight $w = QD_j$, representing its impact on product performance or customer satisfaction.

Step 3: Construct the Relationship Matrix R

The relationship matrix R quantifies the interaction between each TA and QD. Experts assess the effect of each TA on each QD using a scoring system ranging from –9 (strongly negative) to +9 (strongly positive), with intermediate values 3, 1, 0, –1, –3 for weaker relationships. These assessments are averaged across experts and recorded in matrix R.

Step 4: Determine Weights Using AHP

To ensure consistency and objectivity, the Analytic Hierarchy Process (AHP) is used to compute the final weights for both TAs and QDs. This structured technique transforms pairwise comparisons into normalized weight vectors and ensures acceptable consistency (CR ≤ 0.1), following Saaty's method[28].

Step 5: Compute the Correlation Matrix S

The relationship matrix R and TA weights calculate the correlation matrix S, representing the degree of interaction between pairs of QDs.

$$S_{xy} = \sum_{i=1}^{m} [R_{ix}\, w(TA_i).(R_{iy}.w(TA_i)$$

$$= \sum_{i=1}^{m} R_{ix}.R_{iy.}w^2(TA_i), x, y = 1,2\,,,n, x \neq y$$

$$= [S_{xy}] \qquad (1)$$

Where:

m is the number of technical attributes,

R_{ix}; R_{iy} are relationships of TA_i QD_x and QD_y ,

$w(TA_i)$ is the weight of the technical attribute.

This matrix is visualized as the "roof" in the HoQ model, capturing synergistic or conflicting relationships among Quality Dimensions (QDs).

Step 6: Build the DTM chains according to the production process sequences.

For complex production environments, such as the particleboard industry, where multiple modules exist (e.g., forming, hot press, sanding), each module has its own DTM. These are aggregated into a DTM chain, where relationship matrices are aligned diagonally in sequence. This enables tracking the propagation and interaction of defects across modules, which is crucial in MCP contexts. The DTM chains are illustrated in Figure 3.

2.3. Significance and Further Integration

The DTM provides a comprehensive and scalable foundation for predictive quality control, particularly when integrated with data-driven methods, such as principal component analysis (PCA). It enables engineers to prioritize process improvements, isolate high-impact root causes, and prepare the data structure for further study. The DTM method is recognized as a powerful approach to link process operations with defect outcomes, offering a

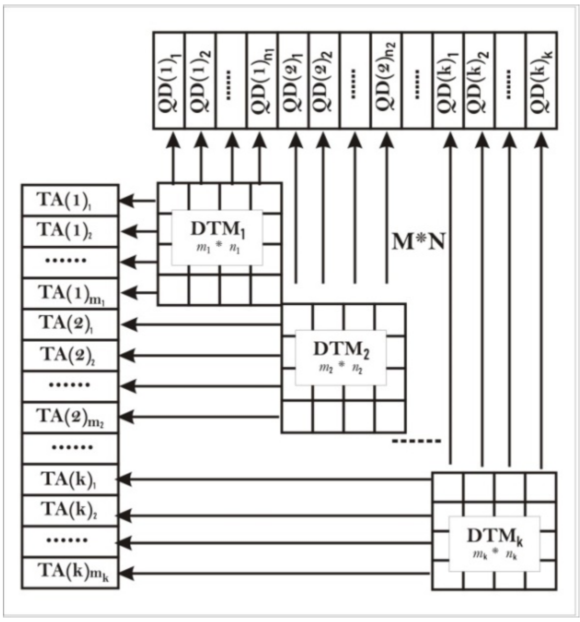

Fig. 3: DTM Chains

structured path toward implementing Zero Defect Manufacturing (ZDM) principles in modular production systems. It is acknowledged that the construction of the TA–QD relationship matrix relies primarily on expert judgment, which inherently introduces the potential for subjectivity and inconsistency. To mitigate this, the Analytic Hierarchy Process (AHP) was employed to standardize evaluations and ensure consistency across respondents, with consistency ratios (CR $\leq$ 0.1) strictly enforced. Nonetheless, the absence of sensor-based or real-time operational data limits the objectivity and adaptability of the current model. Future work should explore the integration of machine-generated data streams, such as vibration signals, temperature logs, or visual inspections via computer vision systems, to support or validate the expert-based assessments.

This methodological positioning aligns with multi-criteria optimization approaches widely adopted in manufacturing research. For example, a rigorous integration of Response Surface Methodology (RSM) and desirability functions has been applied to optimize machining performance of metal matrix composites, illustrating how statistical optimization techniques can complement defect detection frameworks like the proposed DTM–PCA model by providing robust parameter tuning for improved process outcomes [29)].

2.4. DTM downsizing with PCA

As the complexity of the Defect Tracking Matrix (DTM) grows with the number of technical attributes (TAs) and quality defects (QDs), analyzing the full matrix can become computationally intensive and cognitively overwhelming. To address this, Principal Component Analysis (PCA) is applied to reduce the dimensionality of the DTM without sacrificing key information. PCA

	QD1	QD2	QD3	QD4
QD1		3.23	6.10	00.00
QD2	3.23		5.04	00.00
QD3	6.10	5.04		00.00
QD4	00.00	00.00	00.00	

	QD1	QD2	QD3	QD4
QD1	15.08	3.23	6.10	00.00
QD2	3.23	4.08	5.04	00.00
QD3	6.10	5.04	8.35	00.00
QD4	00.00	00.00	00.00	

Fig. 4: Diagonal calculation of the QD relationship matrix

transforms the original high-dimensional DTM into a lower-dimensional structure that retains the most significant patterns[19)]. The PCA-based dimensionality reduction process begins by transposing the relationship matrix R and incorporating the technical attribute weights $w(TA_i)$ to construct a TA–QD correlation matrix. This forms the mathematical basis for calculating the "roof" of the DTM structure, capturing indirect QD relationships. The procedure for simplifying the DTM with PCA is as follows[21)].

Transpose of the correlation R and weight values to construct the TA and QD relationship matrix. This will enable the recalculation of the ceiling matrix values for each TA and QD relationship matrix, as shown in the appendix (Figure A8).

Calculate the diagonal of the TA and QD relationship matrix using the following formula:

$$S_{xy} = \sum_{i=1}^{m}[R_{ix}.w(TA_i).(R_{iy}.w(TA_i)]\ x = y \qquad (2)$$

An example of diagonal calculation of the TA–QD relationship matrix using Eq. (2) is shown in Figure 4.

Calculate the CMI (Indeks Criterion of Mode Importance) value.

Calculate eigenvalues and eigenvectors using the MATLAB application.

Determine the number of new matrices to be selected and eliminate criteria with eigenvalues >1.

Multiply the eigenvalue by each eigenvector.

Find the largest multiplication value and determine the matrix according to the specified amount.

Create of a new DTM Chain.

Recent studies have employed matrix-based traceability tools and principal component analysis (PCA) in manufacturing quality control, enabling real-time monitoring and dimensionality reduction. For instance, Chen et al.[30)] reviewed a broad spectrum of surface defect detection techniques, highlighting the role of dimensionality reduction in improving classification performance. Adeyemi[31)] proposed a deep learning framework that combines feature extraction and thresholding for accurate defect prediction, while Liu et al.[32)] introduced a generative model integrated with one-class classification to detect surface anomalies in unsupervised environments. Complementing these efforts, Rahman et al.[33)] demonstrated how predictive spatial analysis using PCA-based metrics can enhance control precision in high-speed combustion applications. Additionally, Kumar et al.[34] applied PCA within a hybrid Taguchi–GRA optimization scheme to reduce data complexity and prioritize quality parameters in composite materials. Collectively, these studies support the integration of PCA into DTM-based frameworks for efficient dimensionality reduction and enhanced interpretability in predictive quality control systems.

To support component selection, a scree plot was generated for the Forming Area (Appendix: Figure A1), which clearly reveals an elbow point at the third component. While scree plots for the Pre-Press and Press areas are not shown, the eigenvalue patterns in those areas similarly indicate a sharp drop after the third component, validating consistent dimensionality across stages. This consistency suggests structural stability in the TA–QD relationship across the process chain and supports the methodological robustness of the PCA.

3. Case study and results

An existing particle board company in Indonesia will implement the detection technique for achieving Zero Defect Manufacturing (ZDM) through the Defect Tracking Matrix (DTM). PT Kutai Timber Indonesia operates within the wood processing sector, with particle board constituting one of its three divisions. Particleboards are produced by turning scrap wood into solid boards suitable for home use, either through lamination or plywood coating. Research has yielded data regarding the technical features and quality defects of particle board products at PT. Kutai Timber Indonesia.

The data collection process was conducted within the Particleboard Division of PT Kutai Timber Indonesia between October and December 2024. Multiple methods were employed to ensure data credibility, including direct observation of operations, structured interviews with production and quality staff, document analysis, and questionnaire distribution. The resulting dataset captures a wide range of technical attributes and surface defect occurrences over various operational conditions and production cycles, ensuring robustness and relevance for the analysis, as shown in Table 2.

Based on Table 2, several technical attributes were identified as significant contributors to product defects. For instance, improper duct cleaning (TA1) is strongly correlated with dust spot defects (QD1), whereas inaccurate press calibration (TA7) leads to thin spot defects (QD6). Similarly, errors in blade sharpening (TA11) result in corrugated cutting defects (QD9). These relationships suggest that production parameters, such as equipment maintenance, process calibration, and material handling, have a direct influence on the occurrence of defects. By identifying these attributes, manufacturers can proactively adjust their production settings to minimize defects and achieve zero defects and maximum yield (ZDM).

Table 2: Techniques Attribute (TAs) and Quality Defects (QDs).

		Forming area		
No	Techniques Attribute	$(\boldsymbol{TAs})$	Quality Defects	$(\boldsymbol{QDs})$
1	Duct Cleaning	TA 1	Dust Spot	QD 1
2	Setting section	TA 2	Rough surface	QD 2
3	Setting Blower	TA 3	Core Showing	QD 3
4	Screen Cleaning	TA 4	Crack	QD 4
5	Nozzle hardener	TA 5		
		Hot Press		
No	Techniques Attribute	$(\boldsymbol{TAs})$	Quality Defects	$(\boldsymbol{QDs})$
1	Shimming	TA 6	Sanding Leakage	QD 5
2	Press Calibration	TA 7	Thinspot	QD 6
3	Transducer Setting	TA 8	Oil stains	QD 7
4	Hammering	TA 9	Blister	QD 8
5	Protection Cleaning	TA 10		
		Cut to size		
No	Techniques Attribute	$(\boldsymbol{TAs})$	Quality Defects	$(\boldsymbol{QDs})$
1	Blade Sharpening	TA 11	Corrugated Cutting	QD 9
2	Pusher setting	TA 12	Over Diagonal	QD 10
3	Blade setting	TA 13	length and width cuts	QD 11
4	Stopper setting	TA 14	Little damaged	QD 12
5	Sensor Calibration	TA 15		
		Sanding Machine		
No	Techniques Attribute	$(\boldsymbol{TAs})$	Quality Defects	$(\boldsymbol{QDs})$
1	Sand Paper	TA 16	Cutting Mark	QD 13
2	Platten	TA 17	Sharp	QD 14
3	Rubber Setting	TA 18	Crooked sanding	QD 15
4	Pusher	TA 19	Paper stripe	QD 16
5	Sensor tracking	TA 20		

The procedure of DTM for Prediction source of defects:

In this study, 20 (TAs) and 16 (QDs) were obtained, and based on the collected data, a questionnaire was distributed for the DTM data. The distribution of the questionnaire was conducted among five experts at PT KTI, namely the Supervisor of Quality Control, Vice Supervisors of Quality Control, Vice Supervisor of Quality Assurance, and Vice Supervisor of Production. We process the obtained data to create the DTM under the procedure. Determine the weights of (TAs) and (QDs) using the AHP method. Table 3 summarizes the weights of the TAs and QDs as well as the corresponding correlation matrix R for the forming area.

Table 3: The weights of (TAs) and (QDs)

Forming area		
Techniques Attribute	Weight	%
Duct Cleaning	0.322	32
Setting section	0.248	25
Setting Blower	0.204	20
Screen Cleaning	0.129	13
Nozzle hardener	0.097	10
Quality Defects	Weight	%
Dust Spot	0.383	38
Rough surface	0.307	31
Core Showing	0.175	18
Crack	0.135	13
Hot Press		
Techniques Attribute	Weight	%
Shimming	0.358	36
Press Calibration	0.247	25
Tranducer Setting	0.175	17
Hammering	0.128	13
Protection Cleaning	0.092	9
Quality Defects	Weight	%
Leakage Sanding	0.423	42
Thinspot	0.266	27
Oil stains	0.175	17
Blister	0.137	14
Cut to size		
Techniques Attribute	Weight	%
Blade Sharpening	0.404	40
Pusher setting	0.254	25
Blade setting	0.164	17
Stopper setting	0.106	11
Sensor Calibration	0.072	7
Quality Defects	Weight	%
Corrugated Cutting	0.461	46
Diagonal Over	0.236	24
length and width cuts	0.168	17
Little damaged	0.135	13
Sanding Machine		
Techniques Attribute	Weight	%
Sand Paper	0.360	36
Platten	0.264	26
Rubber Setting	0.158	16
Pusher	0.128	13
Sensor tracking	0.090	9
Quality Defects	Weight	%
Cutting the mark	0.455	46
Sharp	0.263	26
Crooked sanding	0.141	14
Paper stripe	0.141	14

The correlation matrix R was calculated to quantify the strength of the relationships between technical attributes (TAs) and quality defects (QDs) in the forming area, as shown in Table 4.

The calculation of the correlation matrix R for the hot press machine, cut-to-size machine, and sanding machine is also provided in the appendix (Appendix: Figure A2, A3, A4). The correlation matrix S was determined, as shown in Figure 5. Figure 5 shows the calculation of the correlation matrix S for the forming area. The calculation of the

Table 4: Correlation Matrix R for the Forming Area

Forming area					
		QD1	QD2	QD3	QD4
1	TA1	-9	0	0	0
2	TA2	-9	-3	-9	0
3	TA3	-3	-9	-9	0
4	TA4	-9	-3	0	0
5	TA5	0	0	0	-9
Total		-30	-15	-18	-9
	QD1	QD2	QD3	QD4	W(TA)
TA1	-9	0	0	0	0.322
TA2	-9	-3	-9	0	0.248
TA3	-3	-9	-9	0	0.204
TA4	-9	-3	0	0	0.129
TA5	0	0	0	-9	0.097
W(QD)	0.383	0.307	0.175	0.135	

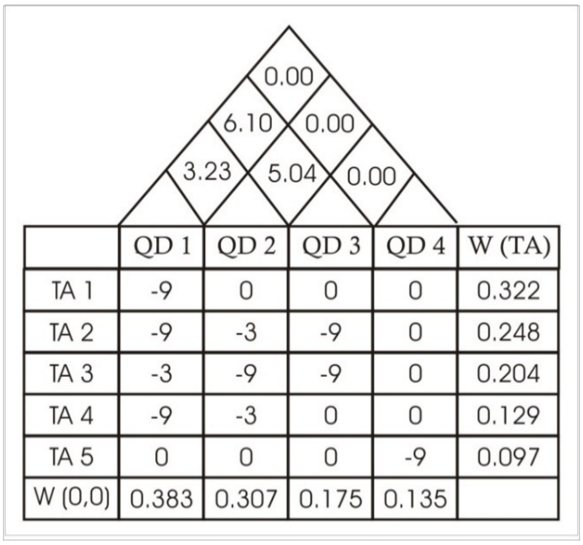

Fig. 5: The correlation matrix S (Forming Area)

correlation matrix S for the hot press machine, cut-to-size machine, and sanding machine is also provided in the appendix (Appendix: Figure A5, A6, A7).

Build the DTM chains according to the production process sequence, as shown in the appendix (Figure A11).

3.1. DTM downsizing with PCA

The DTM matrix is complex and still inefficient, so a simplification is carried out using the PCA method to make it more efficient and effective. The DTM procedure processes the data before performing the simplification steps using the principal component analysis (PCA) method, as shown in the appendix (Figure A8)

The process involves creating a TA relationship matrix by transferring the correlation matrix S or the roof matrix into a 5x5 matrix, which is necessary because there are 5 TAs in the Forming area, as shown in the appendix (Figure A10) and QD relationship matrix (Figure A9).

Figure 6 illustrates an example of how the remaining unfilled diagonals of the 5×5 matrix are completed. Calculate the diagonals of the 5x5 matrix to complete the

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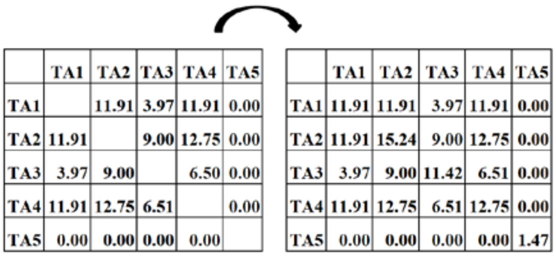
diagonals that are still unfilled, as shown in Figure 6. The next step is to calculate the CMI value, eigenvalues, and eigenvectors using the MATLAB application. The data entered into MATLAB are the TA correlation matrix data with a complete diagonal, as shown in Table 5.

The next step is the elimination of the matrix with an eigenvalue of < 1 so that the remaining TA 3, TA 4, and TA 5 columns are obtained, as shown in Table 6. Multiplying all the vector eigenvalues by each of their eigenvalues, the following results are obtained (Table 7).

Choose the result of the largest multiplication from Table 7 so that the selected ones are TA 1, TA 2, and TA 4. We selected 3 TAs because the rest of the elimination left 3 columns, so we also chose the 3 rows with the largest multiplication, as shown in Table 8.



	TA1	TA2	TA3	TA4	TA5
TA1		11.91	3.97	11.91	0.00
TA2	11.91		9.00	12.75	0.00
TA3	3.97	9.00		6.50	0.00
TA4	11.91	12.75	6.51		0.00
TA5	0.00	0.00	0.00	0.00	

	TA1	TA2	TA3	TA4	TA5
TA1	11.91	11.91	3.97	11.91	0.00
TA2	11.91	15.24	9.00	12.75	0.00
TA3	3.97	9.00	11.42	6.51	0.00
TA4	11.91	12.75	6.51	12.75	0.00
TA5	0.00	0.00	0.00	0.00	1.47

Fig. 6: Calculation of the diagonal of the TAs

Table 5: Eigenvalues and eigenvector TAs forming

	TA 1	TA 2	TA 3	TA 4	TA 5
CMI (%)	-0.01	1.77	2.78	15.8	79.6
Eigenvalues	-0.006	0.935	1.470	8.351	42.039
Eigenvectors	-0.736	0,076	0.000	0.459	0.491
	0.278	-0,755	0.000	-0.063	0.591
	-0.277	0.245	0.000	-0.860	0.351
	0.551	0.604	0.000	0.212	0.535
	0.000	0.000	1.000	0.000	0.000

Table 6: Elimination Eigenvalues

	TA 3	TA 4	TA 5
CMI	2.78%	15.82%	79.63%
Eigenvalues	1.47	8.3514	42.0388
Eigenvectors	0	0.4591	0.4913
	0	-0.0628	0.5908
	0	-0.8603	0.3511
	0	0.2124	0.535
	1	0	0

Table 7: Multiplying eigenvalues and eigenvectors

	TA 3	TA 4	TA 5
TA1	0.00	3.83	20.65
TA2	0.00	-0.52	24.84
TA3	0.00	-7.18	14.76
TA4	0.00	1.77	22.49
TA5	1.47	0.00	0.00

The last step is to compile a new DTM chain that is obtained from simplification using PCA, as shown in the appendix (Figure A12)

Table 8: The result of simplification of the DTM

	TA 3	TA 4	TA 5	
TA1	0.000	3.834	20.654	*
TA2	0.000	-0.524	24.837	*
TA3	0.000	-7.185	14.760	
TA4	0.000	1.774	22.491	*
TA5	1.470	0.000	0.000	

Principal Component Analysis (PCA) successfully reduced the dimensionality of the DTM by extracting only the top three principal components from the original 20 technical attributes. These three components retained a cumulative variance of 98.2%, indicating that most of the original information was preserved while simplifying the input structure. This reduction greatly decreases the computational complexity and enhances the interpretability of the DTM framework in a practical setting.

4. Discussion

The findings of this study highlight the practical applicability of combining the Defect Tracking Matrix (DTM) and Principal Component Analysis (PCA) in a real-world manufacturing environment. Compared to traditional quality control methods that rely solely on defect detection or corrective action, this integrated approach introduces a proactive strategy for identifying root causes and reducing quality defects before they escalate. In the context of the particleboard industry, where production involves multiple process stages and complex variables, the DTM served as an effective tool for mapping out the relationship between technical attributes and observed defects. The subsequent application of PCA allowed the simplification of this complex matrix by isolating key contributors that significantly affect defect patterns. This not only enhances interpretability but also enables targeted corrective actions that align with Zero Defects Manufacturing (ZDM) goals.

The results are consistent with previous studies that advocate for the integration of statistical tools and expert knowledge in quality management systems. For instance, earlier works on defect prediction using neural networks or support vector machines have shown success in generalization but often lack transparency in model interpretation. In contrast, the DTM-PCA method maintains a balance between model simplicity, expert validation, and interpretive clarity. Similar statistical modeling approaches have also been successfully applied in other manufacturing contexts, such as optimizing weld strength in dissimilar aluminum alloys joined via Friction Stir Welding (FSW) using the Response Surface Methodology (RSM) framework, demonstrating the adaptability of such methods for diverse production environments[35)]

Moreover, this framework can be adapted to other sectors beyond wood-based manufacturing, such as the automotive, electronics, or textiles industries, where defect causality is multi-dimensional and interdependent. However, one limitation of this study is the reliance on expert judgment in defining the initial DTM relationships. While this ensures contextual accuracy, it introduces subjectivity, which may be mitigated by integrating real-time sensor data or adaptive machine-learning algorithms in future implementations.

While the DTM–PCA framework was designed with predictive capabilities in mind, the current study did not include statistical validation using actual defect outcome data or historical monitoring. As a result, performance metrics such as accuracy, recall, and precision have not yet been assessed. This is recognized as a limitation of the current phase. Future work will focus on the integration of time-stamped defect logs and machine learning-based validation pipelines to quantify predictive accuracy and ensure real-world applicability of the model.

This study is primarily focused on surface-level quality defects, such as sanding inconsistencies, cutting marks, and core exposure, due to their visibility and impact on customer perception. However, it is acknowledged that other dimensions of particleboard quality—such as mechanical strength, internal density uniformity, and moisture content—are equally critical but remain unaddressed in the current model. These aspects often require destructive or sensor-based testing, which was beyond the scope of this initial DTM–PCA framework. Future studies are encouraged to incorporate such multi-dimensional quality parameters by integrating mechanical test data, humidity logs, or embedded IoT sensors for a more comprehensive predictive control model.

The PCA results reveal that the first principal component (PC1) is predominantly influenced by attributes related to pre-press operations, such as blower setting, screening, and duct cleaning. This indicates that variations in surface defect patterns are strongly linked to upstream process performance. The second principal component (PC2) reflects pressing calibration and glue distribution, which are crucial for defect minimization during thermal bonding. From an operational standpoint, these findings suggest that quality control efforts should prioritize the monitoring and standardization of pre-press parameters. For instance, ensuring proper maintenance of blower systems and consistent glue spray rates can substantially reduce visual defects. These insights support more focused preventive maintenance and calibration procedures, potentially lowering rework and rejection rates. In parallel, advancements in composite material engineering also highlight the role of reinforcement strategies in improving performance outcomes. For example, aluminum surface composites reinforced with graphene via friction stir processing have demonstrated notable improvements in morphology and mechanical behavior, underscoring the potential of material-level interventions to complement process-based defect reduction frameworks[36)]

4.1. Managerial Implications

From a managerial standpoint, the DTM–PCA framework offers a practical decision-support tool by identifying the most influential technical attributes contributing to surface defects. Although PCA transforms the original attributes into principal components, the loading matrix allows reverse mapping, enabling managers to trace which specific operations (e.g., blower calibration, glue spraying, duct cleaning) dominate each component. This interpretability was validated through discussions with the quality assurance team at PT Kutai Timber Indonesia, who confirmed that the PCA-derived insights aligned with their operational experience. Furthermore, considering human-centric perspectives in manufacturing environments can play a vital role in sustaining quality improvement efforts. Studies analyzing human performance under varying environmental conditions—such as those evaluating small-unit air conditioning systems in industrial design centers—demonstrate that workplace ergonomics and environmental control directly influence productivity and defect prevention[37)]. By prioritizing these high-impact variables, managers can allocate resources more efficiently and implement targeted preventive actions, thereby supporting proactive quality control strategies.

5. Conclusions

This study demonstrated the successful application of a combined approach using the Defect Tracking Matrix (DTM) and Principal Component Analysis (PCA) to identify the root causes of surface defects in particleboard manufacturing. The integration of these two methods resulted in a more structured and effective quality control system capable of supporting predictive analysis within the framework of Zero Defect Manufacturing (ZDM). By organizing multiple DTM matrices into a unified DTM chain and applying PCA for dimensionality reduction, a simplified yet informative representation was obtained. This restructured DTM chain facilitated clearer defect traceability and enabled the identification of key technical attributes contributing to quality issues. The predictive capability of the proposed model supports early intervention and continuous improvement in defect management, aligning directly with the objectives of ZDM.

Future research should explore the integration of this DTM–PCA framework with Industry 4.0 technologies, particularly artificial intelligence (AI) and machine learning (ML) algorithms, to enhance its adaptability and predictive accuracy. In addition, expanding the scope beyond surface-level defects to incorporate internal quality attributes—such as mechanical strength, density uniformity, and moisture content—would further increase the model's applicability across different quality dimensions. Moreover, adopting a human-centric approach that enables collaboration between operators and intelligent systems may further strengthen defect prevention strategies and drive sustainable manufacturing excellence.

In conclusion, this study contributes to the growing body of knowledge on predictive quality control by proposing an interpretable DTM–PCA framework tailored to the wood-processing sector. The findings not only provide technical insights into defect drivers but also offer practical value for operational decision-making, thus supporting continuous improvement and Zero Defect Manufacturing (ZDM) initiatives.

Acknowledgments

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Appendix

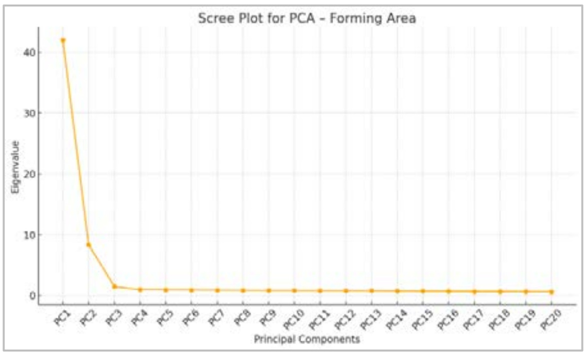


Fig. A1: Scree plot of PCA eigenvalues in Forming Area, showing an elbow point at Component 3.

The correlation matrix R calculations for the hot press, cut-to-size, and sanding machines are presented as follows:

	Hot Press		QD 5	QD 6	QD 7	QD 8	
1		TA 6	-9	-3	0	0	
2		TA 7	-9	-3	0	-1	
3		TA 8	0	0	-9	-1	
4		TA 9	-3	-9	0	0	
5		TA 10	-9	-9	0	0	
		TOTAL	-30	-24	-9	-2	

	QD 5	QD 6	QD 7	QD 8	W (TA)
TA 6	0.30	0.13	0.00	0.00	0.358
TA 7	0.30	0.13	0.00	0.50	0.247
TA 8	0.00	0.00	1.00	0.50	0.175
TA 9	0.10	0.38	0.00	0.00	0.128
TA 10	0.30	0.38	0.00	0.00	0.092
W (Q,D)	0.423	0.266	0.175	0.137	

Fig. A2: The correlation matrix R calculations for the hot press

	Cut To Size		QD 9	QD 10	QD 11	QD 12	
1		TA 11	-9	-3	0	-9	
2		TA 12	-1	-9	-9	0	
3		TA 13	-9	0	-9	-9	
4		TA 14	0	-1	0	-9	
5		TA 15	0	0	-9	-9	
		TOTAL	-19	-13	-27	-36	

	QD 9	QD 10	QD 11	QD 12	W (TA)
TA 11	0.47	0.23	0.00	0.25	0.404
TA 12	0.05	0.69	0.33	0.00	0.254
TA 13	0.47	0.00	0.33	0.25	0.164
TA 14	0.00	0.08	0.00	0.25	0.106
TA 15	0.00	0.00	0.33	0.25	0.072
W (Q,D)	0.461	0.236	0.168	0.135	

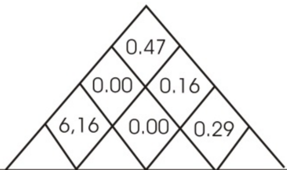
Fig. A3: The correlation matrix R calculations for the Cut to Size

	Sanding		QD 13	QD 14	QD 15	QD 16	
1		TA 16	-9	0	-3	-3	
2		TA 17	-9	-9	0	-3	
3		TA 18	-1	-1	-9	0	
4		TA 19	0	0	-9	0	
5		TA 20	0	0	0	-9	
		TOTAL	-19	-10	-21	-15	

	QD 13	QD 14	QD 15	QD 16	W (TA)
TA 16	0.47	0.00	0.14	0.20	0.360
TA 17	0.47	0.90	0.00	0.20	0.264
TA 18	0.05	0.10	0.43	0.00	0.158
TA 19	0.00	0.00	0.43	0.00	0.128
TA 20	0.00	0.00	0.00	0.60	0.090
W (Q,D)	0.455	0.263	0.141	0.141	

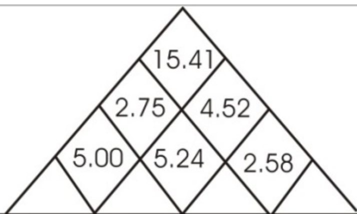
Fig. A4: The correlation matrix R calculations for sanding machines

The correlation matrix S for the hot press, cut-to-size, and sanding machines are presented as follows:



	QD 5	QD 6	QD 7	QD 8	W (TA)
TA 6	-9	-3	0	0	0.363
TA 7	-9	-3	0	-1	0.228
TA 8	0	0	-9	-1	0.179
TA 9	-3	-9	0	0	0.138
TA 10	-9	-9	0	0	0.092
W (Q,D)	0.423	0.266	0.175	0.137	

Fig. A5: The correlation matrix S for the hot press



	QD 9	QD 10	QD 11	QD 12	W (TA)
TA 11	-9	-3	0	-9	0.404
TA 12	-1	-9	-9	0	0.254
TA 13	-9	0	-9	-9	0.164
TA 14	0	-1	0	-9	0.106
TA 15	0	0	-9	-9	0.072
W (Q,D)	0.461	0.236	0.168	0.135	

Fig. A6: The correlation matrix S for cut-to-size

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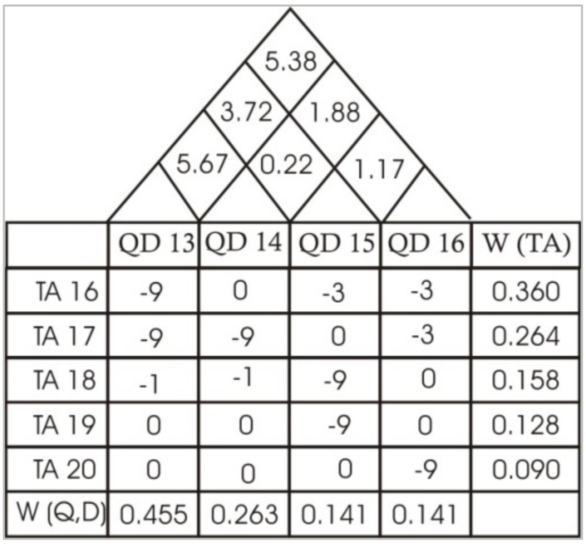
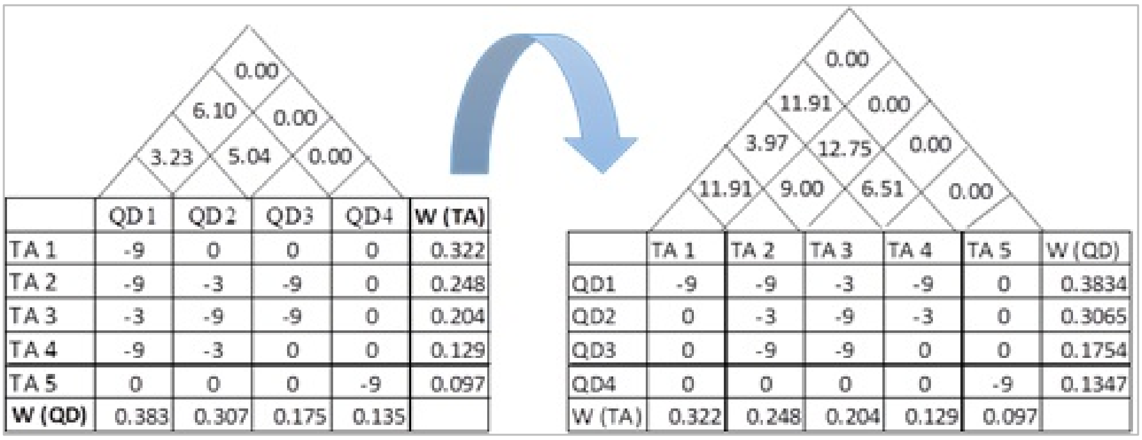


	QD 13	QD 14	QD 15	QD 16	W (TA)
TA 16	-9	0	-3	-3	0.360
TA 17	-9	-9	0	-3	0.264
TA 18	-1	-1	-9	0	0.158
TA 19	0	0	-9	0	0.128
TA 20	0	0	0	-9	0.090
W (Q,D)	0.455	0.263	0.141	0.141	

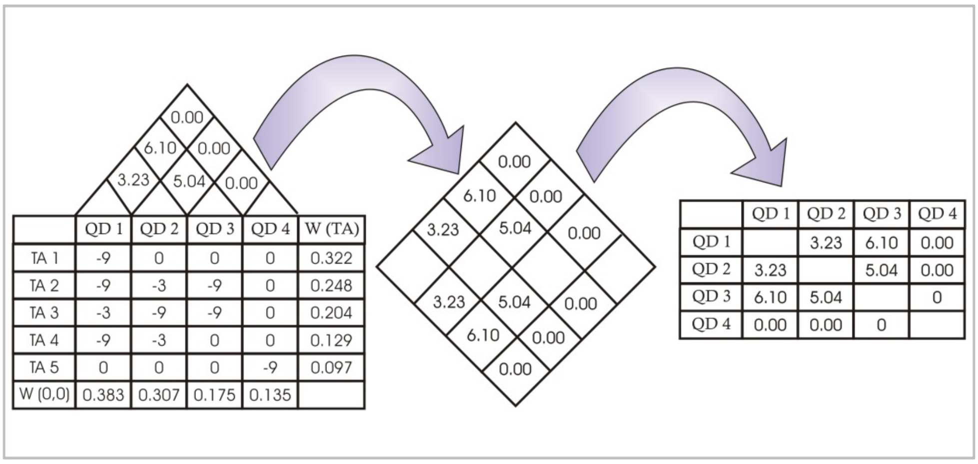
Fig. A7: The correlation matrix S for the Sanding



	QD1	QD2	QD3	QD4	W (TA)
TA 1	-9	0	0	0	0.322
TA 2	-9	-3	-9	0	0.248
TA 3	-3	-9	-9	0	0.204
TA 4	-9	-3	0	0	0.129
TA 5	0	0	0	-9	0.097
W (QD)	0.383	0.307	0.175	0.135	

	TA 1	TA 2	TA 3	TA 4	TA 5	W (QD)
QD1	-9	-9	-3	-9	0	0.3834
QD2	0	-3	-9	-3	0	0.3065
QD3	0	-9	-9	0	0	0.1754
QD4	0	0	0	0	-9	0.1347
W (TA)	0.322	0.248	0.204	0.129	0.097	

Fig. A8: Transpose the QD matrix to TAs



	QD 1	QD 2	QD 3	QD 4	W (TA)
TA 1	-9	0	0	0	0.322
TA 2	-9	-3	-9	0	0.248
TA 3	-3	-9	-9	0	0.204
TA 4	-9	-3	0	0	0.129
TA 5	0	0	0	-9	0.097
W (0,0)	0.383	0.307	0.175	0.135	

	QD 1	QD 2	QD 3	QD 4
QD 1		3.23	6.10	0.00
QD 2	3.23		5.04	0.00
QD 3	6.10	5.04		0
QD 4	0.00	0.00	0	

Fig. A9: Relationship matrix QD

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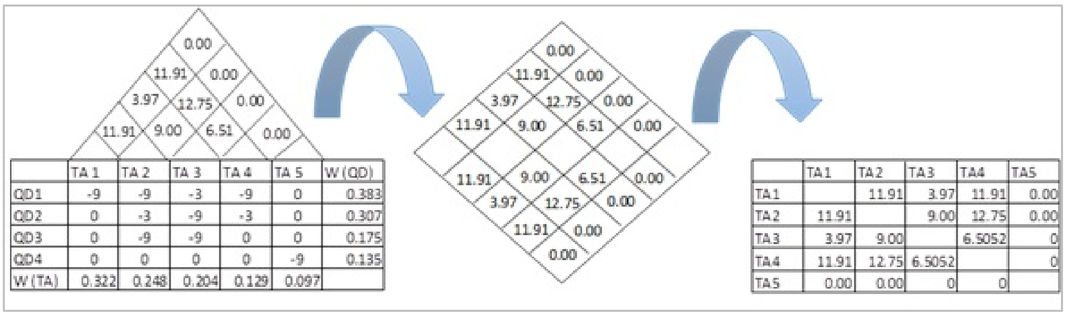

Fig. A10: Correlation matrix TAs

Figure of the DTM chains is presented as follows:

	QD1	QD2	QD3	QD4	QD5	QD6	QD7	QD8	QD9	QD10	QD11	QD12	QD13	QD14	QD15	QD16
TA1	0.30	0.00	0.00	0.00												
TA2	0.30	0.20	0.50	0.00												
TA3	0.10	0.60	0.50	0.00												
TA4	0.30	0.20	0.00	0.00												
TA5	0.00	0.00	0.00	1.00												
TA6					0.30	0.13	0.00	0.00								
TA7					0.30	0.13	0.00	0.50								
TA8					0.00	0.00	1.00	0.50								
TA9					0.10	0.38	0.00	0.00								
TA10					0.30	0.38	0.00	0.00								
TA11									0.47	0.23	0.00	0.25				
TA12									0.05	0.69	0.33	0.00				
TA13									0.47	0.00	0.33	0.25				
TA14									0.00	0.08	0.00	0.25				
TA15									0.00	0.00	0.33	0.25				
TA16													0.47	0.90	0.14	0.20
TA17													0.47	0.90	0.00	0.20
TA18													0.05	0.10	0.43	0.00
TA19													0.00	0.00	0.43	0.00
TA20													0.00	0.00	0.00	0.60

Fig. A11: DTM Chains

	QD1	QD3	QD5	QD6	QD8	QD9	QD10	QD12	QD13	QD14	QD16
TA1	0.30	0.00									
TA2	0.30	0.50									
TA4	0.30	0.00									
TA6			0.30	0.13	0.00						
TA7			0.30	0.13	0.50						
TA9			0.10	0.38	0.00						
TA11						0.47	0.23	0.25			
TA12						0.05	0.69	0.00			
TA13						0.47	0.00	0.25			
TA15						0.00	0.00	0.25			
TA17									0.47	0.90	0.20
TA18									0.05	0.10	0.00
TA19									0.00	0.00	0.00
TA20									0.00	0.00	0.60

Fig. A12: A new DTM chain obtained from simplification using PCA