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Article

Perceptron model application for traceability risk in spun pile manufacturing

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Abstract: A precise risk assessment in a production line constitutes a significant item to identify susceptible areas where there is a possibility of product quality degradation. This also applies to the precast concrete production line in Indonesia that has a spun pile product. Based on a risk assessment activity conducted in this study, it is proposed to build a traceability model in order to maintain and even improve the spun pile product quality in Indonesia. The approach used was the Neural Network of the perceptron model for weighing and will result in a defined traceability path in the context of reducing defects and even failed spun pile products. The simulation result showed that the model has been able to detect risky path possibilities to reduce product quality. The accumulation result of high-risk and medium-risk paths in this study showed that closer to product finalization, the risk will be higher. It is evident that when assessing Indicators, the order from the highest accumulation value first is Curing & Demolding and Stressing & Spinning at 29% each, Casting at 14%, Forming & Setting at 14%, and lastly Cutting & Heading at 14%. Regarding the risk assessment for activities, the first position is Curing & Demolding and Stressing & Spinning with 30% each, the second is Casting and Forming & Setting with 15% each, and the third is Cutting & Heading with 10%.

Keywords: traceability path; risk weighing; perceptron; spun pile; precast

1. Introduction

In the Industry 4.0 era, the traceability of products requires an important digital mechanism to have a comprehensive understanding of the process that has occurred. It has an implication on absolute control over quality, effective management, customer complaint analysis, handling of defective products, and reducing inefficiency in production and distribution of responsibilities. This must be based on a planned framework design, technology utilized, and implementation process for product traceability systems in manufacturing. The similarities between traceability systems in the context of design and implementation can be identified in the initial process, however, they will develop dynamically for the most part at a more detailed level. The product traceability system tends to be involved in the many layers of the manufacturing execution system, either on a physical or digital level, making the implementation be a point to be more detailed and complex (Schuitemaker & Xu, 2020).

As a commercialized product at the prefabrication aspect, comprehensive information on the whole life cycle of precast concrete production is a fundamental thing for product quality traceability and handling. It applies from the production phase of products, transportation, storing, until installation. In addition, quality issues often arise, such as the damage level of precast products occurring during various handling procedures after the production process. When a precast product is damaged, but can still be used in the next installation and will have no quality impact on a building structure, it should be taken into account. If the damage that occurred is serious, then the precast product needs to be repaired before being used in construction. Therefore, traceability of the precast product status information becomes significant (Zhu et al., 2021).

One of the precast products or precast concretes is spun pile, which is a type of concrete most frequently ordered by customers and the most common one in production. Spun Pile is a type of deep foundation that is a part of a building and is designed to sustain the structure weight of a building. The challenge of the spun pile production line in Indonesia is the efficiency issue of the production time. This occurs because when there is an increased number of spun pile products demand that must be fulfilled, the completion of such demand often exceeds the agreed time limit. This is because of various limitations such as machine knockdown during the production process, the production of many defective products hence requiring more time to do a rework, not to mention other issues undetected directly. These factors are likely to substantially impede the efficiency of the production process. Studies have been conducted to find solutions for such issues such as using the Total Productive Maintenance (TPM) approach with the effectiveness measuring gauge in the form of Overall Equipment Effectiveness (OEE) and Overall Throughput Effectiveness (OTE) in every machine along the spun pile production path (Purnomo, 2018).

In addition to the above matters, the product quality factor in the production process becomes a vital point to maintain and observe. Quality control of spun pile concrete has a big effect on the spun pile strength, in supporting the strength of a foundation of either buildings or other infrastructures to be built. Spun pile quality must be maintained with quality control including material property tests, mix design, slump tests and compressive strength tests of the test object. Spun pile quality control consists of various material test methods, from rough aggregate to fine aggregate tests, job mix, up to testing on the test object. All of that aims to find out the content of natural materials used to manufacture spun pile products, in order to determine whether it is feasible to be used or not and to find out the quality strength of the spun pile concrete planned. The spun pile manufacturing process is done by utilizing advanced equipment to support the work and maintenance is applied to the products to reduce defective products. From the study result, it can be concluded that material tests in concrete quality control must conform to the standard, product manufacturing must be excellent and of quality, defective products must be handled well and product maintenance must be good (Saputra et al., 2022).

Product traceability is not only done to maintain product quality when spun pile damage occurs. The durability of precast concrete products in the environment including spun piles when installed must still be monitored to improve their quality. This needs to be done as the research is done (E. Brunesi et al., 2018, 2020; Emanuele Brunesi et al., 2019). Certain tests carried out are always based on project monitoring data.

There are many artificial intelligence approaches to neural network models for traceability. Some use NBOW, RNN, CNN, and self-attention models (Dai et al., 2023). There are also deep learning and Fuzzy model approaches (J. Wang et al., 2017; K. Wang et al., 2019). The most utilized using the perceptron model approach is the multi-layer perceptron (De Nadai Fernandes et al., 2022; Fernandes et al., 2022), not the single-layer perceptron as used in this study.

In this paper, the traceability path in the spun pile production method using the Perceptron Neural Network Model approach will be defined and modeled, based on the quantity identification of the risk value of each production phase. Product quality will be able to be maintained, and even improvements in quality and customer service improvement of spun pile products are feasible.

2. Relation work

2.1. Line production risk

Design for manufacturing and assembly is the practice of designing products for manufacturing while considering product design within the shortest time and with the least development cost, ensuring the most optimal transition to production. Assembly and testing are carried out with minimum cost and in the shortest time possible, while maintaining the expected quality and reliability levels. The system examines early in the manufacturing process to shorten product development time, ensure smooth transitions between processes in manufacturing, and expedite product time to market. This process can reduce costs by efficiently assembling products from more standardized raw materials. Parts of the product are designed for ease of fabrication and improved precision (Bayoumi, 2000).

Several studies elaborate on the importance of observing risks in line production because it is necessary for investigating and improving human, machine, environmental, and psychological compatibility. Regardless of the product type, all studies refer to the expected final results, which include ensuring employee health and safety and improving work efficiency (such as reducing idle capacity, increasing production, and improving product quality). All such reasons originate from the premise that deploying healthy and safe workers enables improvements in work efficiency (Realyvásquez-Vargas et al., 2020; Shanta and Semenova, 2019; Soltanali et al., 2020; Tarakci et al., 2020).

The production process, or production path, of spun pile in Indonesia is generally established in a mass fabrication system, passing through several key process phases. These phases include reinforcement assembly, mold assembly, casting, reinforcement stressing, and compacting with spinning system processes. One of the most important aspects of the spun pile production process is its production capacity, which is determined by optimizing each process phase. In the study by Satyadharma (2022), the spun pile production process is outlined as shown in **Figure 1**.

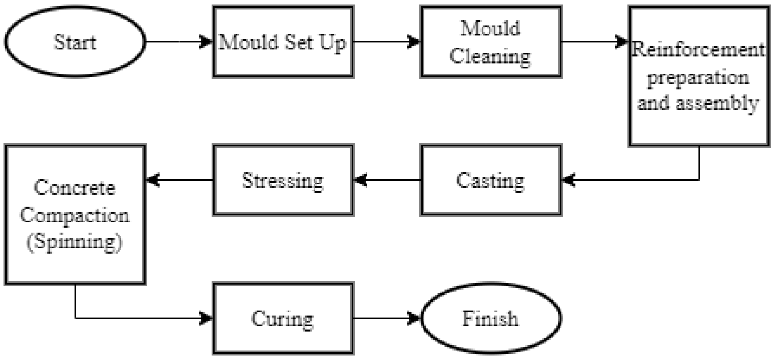

Figure 1. Spun pile production process.

Based on observation and referencing (Andika Okayana, 2023), the sequence can be explained as follows:

(1) Mold setup is an activity of setting up a mold including mold body according to the length or diameter of the spun pile to be produced, and installing nuts and bolts as well as other accessories to the mold.

(2) Mold cleaning entails removing dirt or residue from the concrete mix that may have adhered to the mold during the previous casting process. During this activity, mold lubricant is also applied to the sides of the mold to prevent concrete from sticking and causing crust formation.

(3) Reinforcement preparation and assembly involve tasks such as fitting reinforcement inside the mold, installing connection plates and/or pile shoes, and placing bolts inside the mold.

(4) Casting is performed once the reinforcement assembly is set into the mold. The concrete mix is prepared using a mixer, and it is evenly spread using a cast hopper to ensure conformity with specifications regarding the diameter of the hollow in the spun pile.

(5) Stressing is the process of pulling out prestressing reinforcement from the product.

(6) Concrete compacting for spun pile is done through the spinning process. Spinning is performed by rotating the mold already filled with the concrete mix at a certain speed/RPM to produce the required compactness. The hollow in the spun pile is created as a result of the spinning process.

(7) Curing is performed by putting a mold filled with concrete mix into a curing basin. When the curing basin is full, it is closed. The heat resulting from the concrete hydration process will help accelerate the concrete setting and the mold can be opened after the concrete has aged for a minimum of 8 hours (Handayani, 2020).

2.2. Risk identification for spun pile product

Risk identification is the process of recognizing, finding, or identifying risks. Risks can be identified through sources originating from the risk itself or from the potential impact of losses. Risk identification plays a pivotal role in successfully managing risks. Failure in the risk identification process can lead to problems throughout the entire risk management process, resulting in the failure to achieve organizational goals. Tools and techniques merely facilitate the identification process, and their adoption should be based on the characteristics of the company. The difficulty in recognizing and optimally utilizing applicable tools and techniques within organizations has been identified as one of the main barriers to effective risk management practices (Rostami, 2016).

Every project must be managed through an approach based on production management and project management practices. In projects implemented by manufacturers, this approach is frequently referred to as Project-Oriented Manufacturing. This emphasizes the crucial management and control of equipment in manufacturing production while considering limitations such as time, cost, scope, and quality. Throughout the project's lifecycle and current processes, there are numerous potential risks, both positive and negative, making it important to control this process to prevent negative impacts on project quality (Shirazi, 2021).

The increasing complexity in product design, strict regulations, and market dynamics highlight the vital importance of risk assessment for conducting successful production operations. Failures often occur due to a lack of responsiveness to issues such as raw material shortages, downtime problems, equipment degradation, or other operational challenges that may increase wasted costs. Risk assessment must comprehensively cover the entire company's operations, including external and internal factors. Some risk assessments may prioritize external/supplier factors as the main focus. While the scope of risk assessment at the production line level may not be as broad as that of the supply chain, it still identifies susceptible areas within the production line. This identification helps reduce damages caused when a risk event occurs (Punyamurthula and Badurdeen, 2018).

2.3. Risk measurement survey with spun pile method

The measurement is performed by the means of filling in a survey questionnaire by every personnel involved in every production path of spun pile of the company operating in Indonesia.

The score value is obtained from the average value of the respondents' results. Information on the survey includes:

Production Line: Spun Pile

Respondents: 30

Status: Employee (Supervisor | Machine Operator)

Sex: Male

Age: ± 34 Years Old

Experience: > 10 Years

The final score value is calculated based on the average value of the survey result of impact referring to the equation of:

$$Impact_{\boldsymbol{average}} = \frac{1}{n}\left(\sum_{i=1}^{n} x_i\right) \tag{1}$$

where:

n = respondents,

xi = respondent's answer.

The risk score value is the average risk frequency multiplied by the average risk impact that occurred.

$$Frequency_{\boldsymbol{average}} = \frac{1}{n}\left(\sum_{i=1}^{n} x_i\right) \tag{2}$$

where:

n = respondents,

xi = respondent's answer.

$$Score_{\boldsymbol{risk}} = Impact_{\boldsymbol{average}} \times Frequency_{\boldsymbol{average}} \tag{3}$$

Risk classification will be divided into 3 (three) classes namely: High Risk, Medium Risk and Low Risk

$$Score_{\boldsymbol{risk}} \rightarrow Classification = \begin{cases} High\ Risk \\ Medium\ Risk \\ Low\ Risk \end{cases} \tag{4}$$

The proportion of risk value when calculated on the failure and success of spun pile products from every 100 rods refer to the calculations:

$$High\ Risk_{Prop} = \frac{High\ Risk_{Total}}{High\ Risk_{Total} + Medium\ Risk_{Total} + Low\ Risk_{Total}} \times 100 \tag{5}$$

$$Medium\ Risk_{Prop} = \frac{Medium\ Risk_{Total}}{High\ Risk_{Total} + Medium\ Risk_{Total} + Low\ Risk_{Total}} \times 100 \tag{6}$$

$$Low\ Risk_{Prop} = \frac{Low\ Risk_{Total}}{High\ Risk_{Total} + Medium\ Risk_{Total} + Low\ Risk_{Total}} \times 100 \tag{7}$$

3. Methodology

3.1. Traceability information

Precast concrete construction, specifically spun pile, has a huge potential to boost innovation in a clean, safe, and highly efficient construction method in the industry. However, its supply chain management faces challenges such as fragmentation, poor traceability, and a lack of real-time information. To overcome these challenges, a new blockchain-based information management framework is needed to support the supply chain in the precast concrete industry. This will broaden the application of blockchain in the construction supply chain domain. Eventually, this framework will be validated, and a visualization system will be presented to achieve (1) information-sharing management, and (2) real-time scheduling control. It should be noted that the establishment of real-time scheduling control is not entirely based on blockchain; a model using the perceptron method will be proposed in this study.

The matters mentioned above including the information system to be established must be adjusted for their function and objective as contained in the business regulation. Spun pile business has a business concept ending on customer satisfaction. This relates to transparency and product traceability as well as the production process, which ultimately becomes important to apply. The idea is that traceability leading to transparency will bring goods production to a higher service standard with better control, increased efficiency in the production line and potentially new customer acquisition (Cornelius, 2018).

With the traceability system, it was possible to identify the root causes, for which specific actions were taken. After three months of implementation the percentage was reduced by 15% of the main defect found (León-Duarte et al., 2020). Of course, the impact of costs and human resource needs will also increase in the implementation of this system. The traceability system will be established based on quality parameters specified by standard on the basis as shown in **Figure 1**. The traceability system model proposed is as in **Figure 2**.

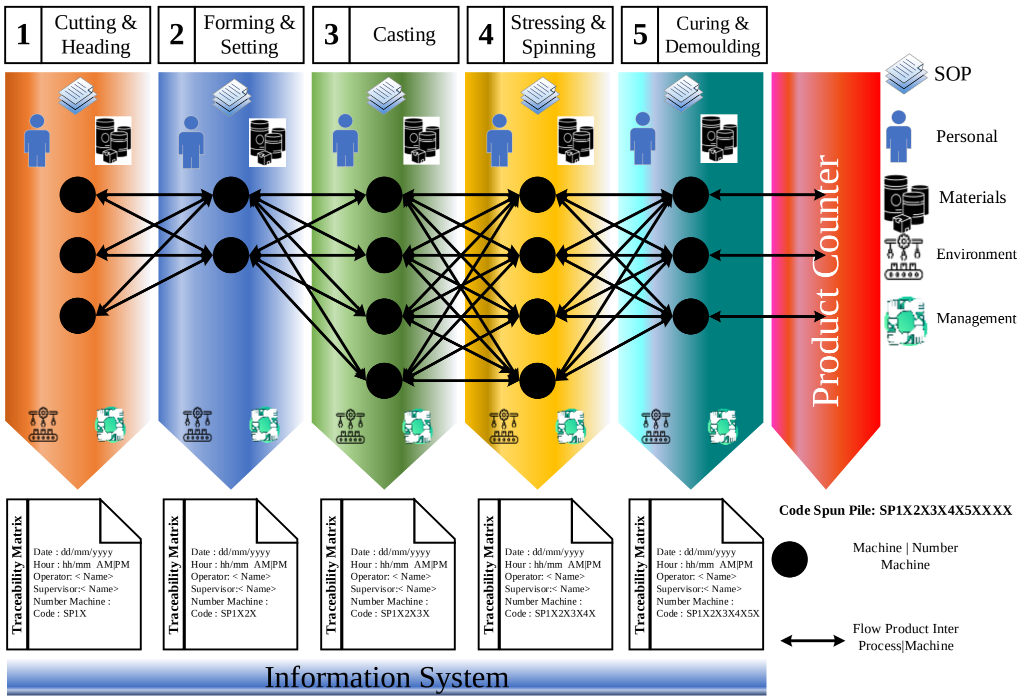

Figure 2. Spun pile spun pile traceability model.

The traceability model will always run its function, monitoring and documenting every production line of spun pile, from the first process to the fifth process with a traceability matrix document serving as the bridge between the production processes adhering to the SOP. Quality control of each part of the production will always be monitored and recorded. Documentation of every subprocess will include information on the responsible personnel and those who work on it, the technology utilized in every subprocess, the working environment at that time, work management procedures, and the materials used in every sub-production.

3.2. Product codification

Based on **Figure 3**, it can be seen that every production subprocess is a subpart of the final product code numbering. Each interface of the traceability document results in an outcome in the form of product code. This means that the final product code is an illustration of a process series happening in a production line.

Codification defined consists of 15-digit combinations of characters and numbers as shown in **Figure 3**.

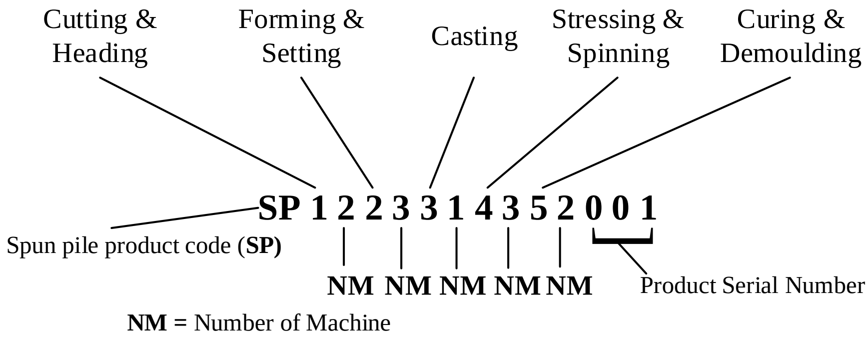

Figure 3. Codification.

Codification of the first two digits of capital letters is the name of the spun pile product (SP), the third digit with number 1 means the Cutting and Heading process and the fourth digit is the number of the Cutting and Heading machine used. The fifth digit with number 2 means the Forming and Setting process and the sixth digit is the number of Forming and Setting machine used. The seventh digit with number 3 is the Casting process and the eighth digit is the number of the Casting machine used. The ninth digit with number 4 means the Stressing and Spinning process and the tenth digit is the number of the Stressing and Spinning machine used. The eleventh digit with number 5 means the Curing and Demolding process and the twelfth digit is the number of the Curing and Demolding machine used. The thirteenth to the fifteenth digits are the sequence of spun pile products produced on the same day.

When a spun pile code is SP1321324151010, it means that the spun pile has been through:

Cutting and Heading in Machine 3
Forming and Setting in Machine 1
Casting in Machine 2
Stressing and Spinning in Machine 1
Curing and Demolding in Machine 2
And it is the tenth product of the day.

3.3. Perceptron

Perceptron is a simple algorithm of the Machine Learning models (Tacchino et al., 2019). Perceptron is commonly used for systems or models that require their output to apply only two conditions. Therefore, perceptron is the algorithm proposed for use in resolving this case. The output of the perceptron algorithm is two conditions: 0 and 1, usually called binary, or −1 and 1, usually called bipolar. Nevertheless, the output still consists of two values or conditions. The algorithm and architecture of the perceptron, according to Lopez-Bernal et al. (2021) are as follows (Algorithm 1):

Algorithm 1 Perceptron Pseudo-code

Input:
Vector x Label 0 = Negative (*N*) input
Label 1 = Positive (*P*) input
Training:
Randomly initialize w misclassification != 0 $x \in N$ and $\sum_{i=0}^{n} w_i$ x $x_i \geq 0$ w = w − x
$x \in P$ and $\sum_{i=0}^{n} w_i$ x $x_i \geq 0$ w = w + x n i=0 wi × xi < 0 w = w + x
Output:
Parameters *w*

The Perceptron model architecture uses a simple perceptron usually called single node perceptron as in **Figure 4** below.

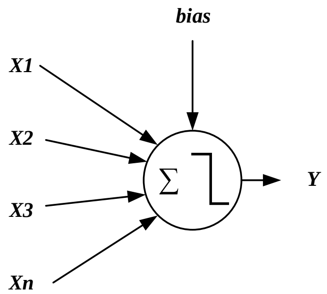

Figure 4. Perceptron architecture.

The perceptron model architecture is one of the artificial intelligence models where it carries out the learning process. Its characteristic is the learning process to determine optimal weighing in the architecture. The weighing is made in order to execute the classification function. There are 2 (two) processes that should occur before the perceptron architecture is implemented. Both processes are learning processes to achieve the architecture's optimal weight and data validation simulation process.

The classification carried out by the perceptron in the traceability process of spun pile products needs the defining of factors or parameters that determine the quality of the products produced. The parameters that must be prepared in advance are related to input and target parameters so that the perceptron architecture can run the learning process for optimal weighing. This process can be seen more clearly in **Figure 5**.

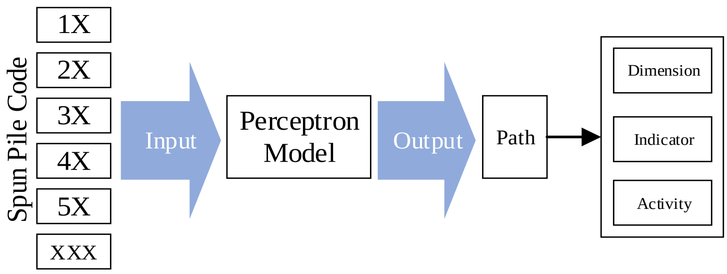

Figure 5. Proposed traceability path model.

In **Figure 5**, the model input based on the product code is identified and decomposed by each digit defined for every subprocess that occurred. The output of the perceptron model will result in the weighing path proportional to the risk of every dimension, indicator and activity.

4. Results

4.1. Risk Identification

The process and survey result analysis has been conducted and risk identification in this study shows findings as presented in **Figure 6** below:

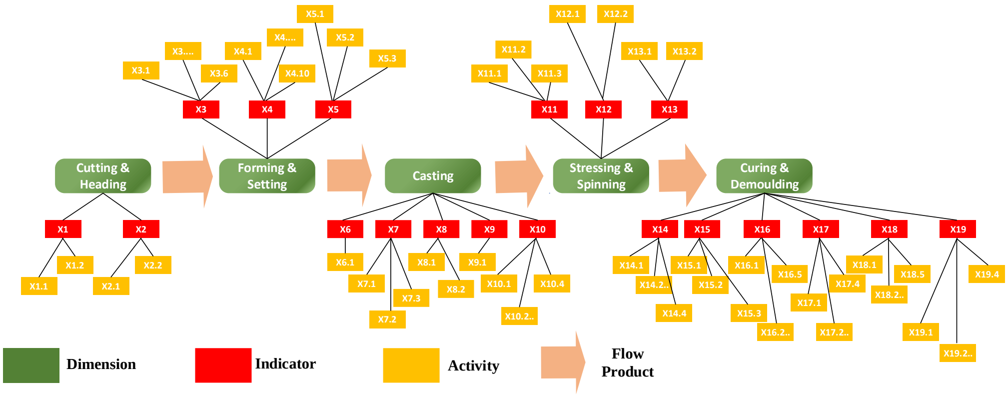

Figure 6. Mapping of risk identification of spun pile production method.

It was identified that there were 66 risky activities from the spun pile production method in manufacturing. The detail is that there were 4 risks at the cutting and heading phase, 19 risks at the forming and setting phase, 11 risks at the casting phase, 7 risks at the stressing and spinning phase and 25 risks at the last phase, which is curing and demolding.

4.2. Scenario design

From **Figures 2** and **6**, a scenario of traceability model function that is fixed can be designed as in **Figure 7** below.

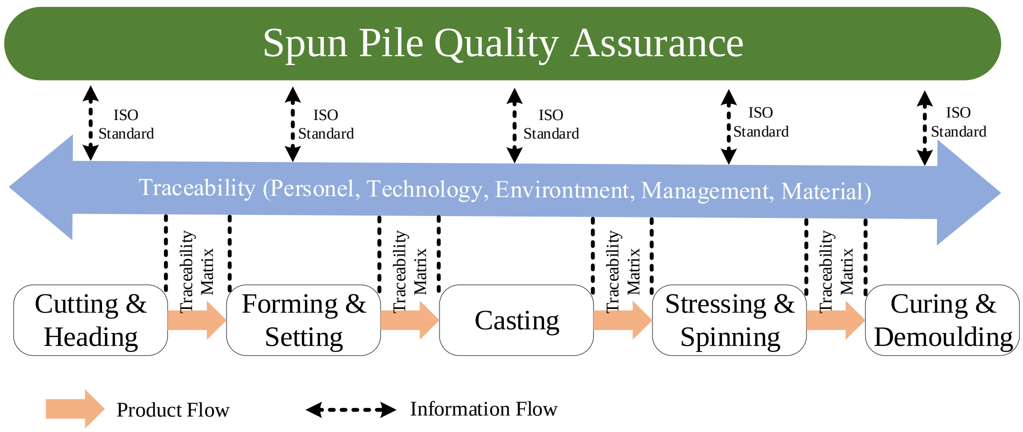

Figure 7. Scenario model of risk traceability function.

Figure 7 shows that the entire process must be able to be traced at each function and procedure. The functions and procedures must be carried out subject to Standard

Operation Procedures (SOP) to maintain the quality of spun pile products manufactured.

The mapping of the risk value that has been calculated according to the survey answers of the respondents in sequence is based on Equations (1)–(3) for each activity as seen in **Figure 8** below:

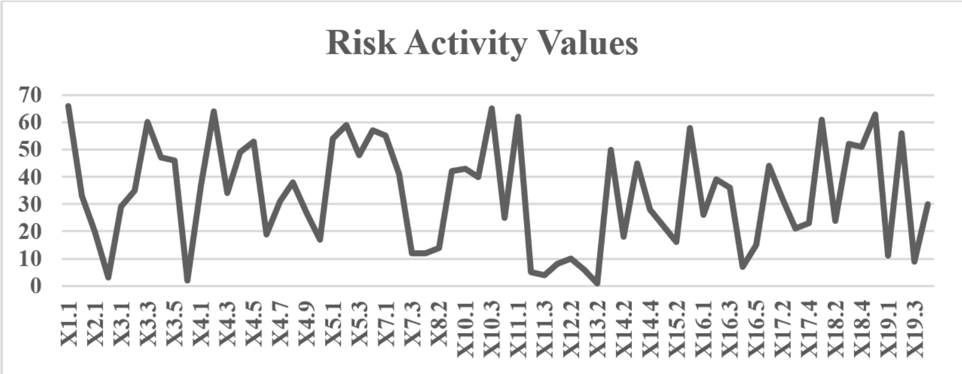

Figure 8. Risk activity value.

Figure 8 shows that the risk value of each activity in the spun pile production method varies. The activity with the highest risk is in activity X.13.2, indicated by X.13 and occurs in the stressing and spinning dimension. The activity with the lowest risk value is in X.1.1, indicated by X.1, in the cutting and heading dimension.

Based on the questionnaire result of the survey conducted by classification (4) approach, it obtained risk assessment from the risk classification quantification for the spun pile manufacturing method as in **Table 1**.

Table 1. Risk assessment result of spun pile manufacturing method.

No	Dimensions	Low Risk	Medium Risk	High Risk
1.	Cutting & Heading	2	1	1
2.	Forming & Setting	16	2	1
3.	Casting	8	3	0
4.	Stressing & Spinning	1	3	3
5.	Curing & Demolding	18	7	0

From **Table 1**, it can be seen that for the initial phase of the spun pile manufacturing method, the quantity of low risk is 35, medium risk is 16 and high risk is 5. This data indicates that the possibility of product failure risk is in order in the processes of Curing & Demolding, Stressing & Spinning, Casting, Forming and setting as well as cutting and heading.

This means that the high and low-risk value weighing is in order of the sequence above. The closer to the final production process, the higher the possibility of failed product risk.

From **Table 1**, values can be calculated based on Equations (5)–(7), to obtain the values shown in **Figure 9** below:

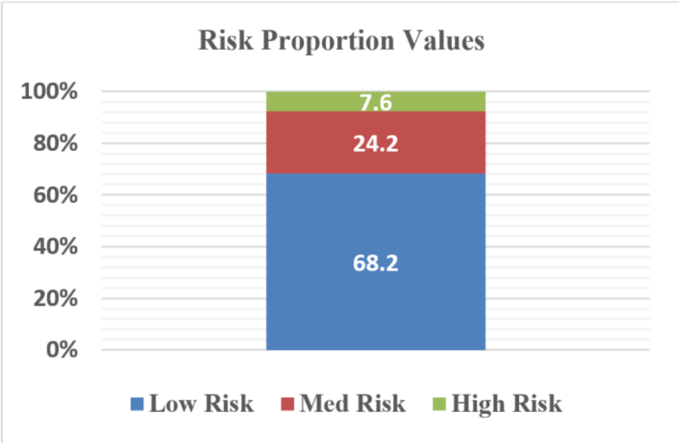

Figure 9. Proportion of risk value of spun pile production method.

Based on **Figure 9**, it can be read that out of 100 rods of spun pile produced, there is the possibility of 24 product failures and 8 defective rods.

On the contrary, from the proportionate results of risk value calculated, the perceptron weighing will confer the highest value in order to the high risk, medium risk then low risk. This is intended so that the risk focus can have a bigger attention hence the quality and success of the product can be higher.

4.3. Traceability model

The traceability model using the perceptron model specifies a reverse risk value weighing with the highest value from the high risk as the previous ground. The input, in the form of product code as in **Figure 5**, instructs the perceptron function to do a reverse tracing (backward) to find out the possibility of risks that may happen in each production process of the spun pile. The tracing results in the proportion of risk value probability mapped as in **Table 2** below.

Table 2. High-risk perceptron path.

No	Dimension	Dimension Values	Indicator Values	Activity Values
1.	Cutting & Heading	1	X2	X2.2
2.	Forming & Setting	1	X3	X3.6
3.	Casting	0	0	0
4.	Stressing & Spinning	1	X11, X13	X11.2, X11.3, X13.2
5.	Curing & Demolding	0	0	0

From **Table 2**, it can be seen that the Perceptron traceability path indicates an extremely high product failure possibility in the stressing and spinning production subprocess by 60%, and in the forming and setting as well as cutting and heading by 20% each.

This means that more attention should be directed to the spun pile production path of activities X11.2, X11.3 and X13.2 under indicators X11 and X13.

The factors of the lowest product failure possibility are Casting and Curing & Demolding. However, this does not mean that the dimension with low product failure possibilities value can be ignored. This should be adjusted to the traceability model decision which must consider medium risk as shown in **Table 3**.

Table 3. Medium risk perceptron path.

No	Dimension	Dimension Values	Indicator Values	Activity Values
1.	Cutting & Heading	1	X2	X2.1
2.	Forming & Setting	1	X4	X4.6, X4.10
3.	Casting	1	X7, X8	X7.3, X8.1, X8.2
4.	Stressing & Spinning	1	X12, X13	X12.1, X12.2, X13.1
5.	Curing & Demolding	1	X14, X15, X16, X19	X14.2, X15.2, X16.4, X16.5, X19.1, X19.3

From **Table 3**, it can be seen that the Perceptron traceability path shows an extremely high possibility of product failure in the Curing & demolding production subprocess by 40%, stressing & spinning and casting by 20%, forming and setting by 13%, and finally cutting and heading by 7%.

This means that more attention should be directed to the spun pile production path of activities X14.2, X15.2, X16.4, X16.5, X19.1 and X19.3 under indicators X14, X15, X16 and X19.

5. Conclusion

The Perceptron will perform traceability based on the weighting of medium-risk and high-risk paths on dimensions valued at 1. This is due to the possibility of significant damage occurring along these paths. Based on the results above, it is evident that the risk pathways defined by perceptrons and mostly traced according to the accumulation of high-risk and medium-risk pathways based on dimensions such as Stressing and Spinning, Forming & Setting and finally Cutting & Heading. These paths have the highest perceptron value weighting by dimensions.

Based on the indicators, the order of the first highest accumulated value is Curing & Demolding and Stressing & Spinning, respectively, at 29%, Casting at 14%, Forming & Setting at 14%, and finally Cutting & Heading at 14%. The perceptron model will define that the greatest possible opportunity in the event of spun pile product failure based on indicators is in the dimensions of Curing & Demolding and Stressing & Spinning, with equal opportunities for indicators in the Casting, Forming & Setting and Cutting & Heading dimensions.

Based on activity, the first rank is held by the Curing & Demolding and Stressing & Spinning dimensions, each at 30%. The second rank is occupied by the Casting and Forming & Setting dimensions, each at 15%, and the third rank is the Cutting & Heading dimension at 10%. The perceptron model will assign a weighting amount according to each percentage value of each dimension.

6. Suggestion

After determining the risk path, every subprocess in the production line of manufacturing spun pile products can be defined, and then the study can continue by tracing defects or quality decline in spun pile products. Model development for the tracing system can be continued until the assessment phase involving project personnel in charge, production process time, technology used, work environment situation, materials used, and management in operation.

For future research, precision can be improved by using images as input in addition to product codes. Images can not only define risks on the production line, but can also detect information on production time and materials properly. This will increase the company's competitiveness in terms of customer satisfaction.

Author contributions: Conceptualization, RH and YL; methodology, VG; software, VG; validation, RH, YL and VG; formal analysis, YL; investigation, RH; resources, YL; data curation, VG; writing—original draft preparation, RH; writing—review and editing, RH; visualization, VG; supervision, YL, VG; project administration, RH; funding acquisition, RH. All authors have read and agreed to the published version of the manuscript.

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Conflict of interest: The authors declare no conflict of interest.

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