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Minimization of Pipe Production Defects using the FMEA method and Dynamic System

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Abstract:

At present, the condition of company engaged in manufacturing iron pipes receives many complaints from consumers because defective products are often found from pipe purchase orders. The risk of production failure determines how the company's process in maintaining production continuity. If the defects are high, the company receives great loss and eventually the production will be disrupted. The purpose of this study is to make a modeling to reduce the risk of failure of the pipe production process. This study identifies the risk of failure using FMEA and dynamic systems in its modeling. The identification results of defects with FMEA in a case study in an iron pipe company are obtained in the form of cracks/breaks from the welding process with the highest percentage of 50%, non-circular pipe 29%, rough surface 15%, and dimensions that do not match 6%. Several policy scenarios related to the risk of failure of the production process are tested to get a percentage of the success of the production process every month with a dynamic system. Exogenous variables from this simulation are the reliability of the machine process and the percentage of rework success. The simulation results show that the optimistic scenario has the largest final product yield of 99% and is followed by an actual simulation result of 96%, a moderate scenario of 90%, and a pessimistic scenario with a success rate of 82%. The developed model can minimize the risk of failure of the iron pipe production process and can be applied in a more complex real world.

Keywords: *Machine Reliability, Optimistic Scenario, Production Process, Percentage of Success Rework*

1. INTRODUCTION

In the rapid development of science and technology, every company is demanded to have good product quality in order to compete with other companies. Product quality is something that can meet consumer expectations.

Companies that produce iron pipes use steel plate raw materials which are generally used for construction such as Line Pipes, Casing & Tubing, Subsea Pipes, Steel Water Pipes, Steel Pipes for Piles and Steel Pipes for General Structures. Current conditions show many complaints from consumers because defective products are often found from pipe purchase orders. This is a serious problem for the management of the pipeline company and they need to immediately take corrective action to overcome the problem of defective product manufactured.

The risk of production failure really determines how the company's process in maintaining production continuity. If the defect is high, the company will receive a loss and the production will be disrupted. It is important to identify the risk of failure so that a handling model can be created to reduce the failure of the production process. The selection of the most suitable selective inspection, partial flow control, and defect correction policy is based on an analysis of the impact of actions on the overall system and the quality performance of the entire process chain, so that quality and productivity can be maintained, at the system level [1].

This study aims to design a model to minimize defects resulting from the production process using a dynamic system, so that this can have an impact on the reduction of the company's defective products.

2. LITERATURE REVIEW

FMEA (Failure Mode and Effect Analysis) is a method used in identifying, assessing risks, and determining risk priorities that must be addressed. The method can be used to effectively determine the possible element failures and errors of a process, system, or design structure. The major objectives of using FMEA are to identify potential failure modes in the system units, evaluate their subsequent effects on system performance, and consequently recommend strategies for eliminating or reducing the chance of occurrence or severity and increasing the detectability of the particular failure mode [2].

The failure referred to in FMEA is anything that causes defects and failures such as defects in work results, product defects or machine failures, so the output or final product produced does not meet the specified standards or specifications.

In general, there are two types of FMEA, FMEA design and FMEA process. In FMEA design, observations are focused on product design. As for the FMEA process, the observation is focused on the activities of the production process.

Identification of potential failures is done by setting a score for each failure mode based on the level of occurrence, severity and detection (Stamatis, 1995). Risk Priority Number (RPN) is a product of the doubling of severity, event level, and detection rate. RPN determines failure priority. This value is used to rank potential process failures. The RPN values are multiplications of severity, occurence and detection [3].

Severity is an assessment of the seriousness of the effects. In that sense, every failure that arises will be assessed on how much the level of seriousness. There is a direct relationship between effect and severity. Severity assessment is an assessment related to how likely there is an impact arising from failure or disability that occurs.

Table 1. Classification of Severity Values

Score	**Criteria**
10	Danger without warning, the system can endanger the operator, the machine qualifications are not in accordance with K3 requirements
9	Danger with warning, the system can endanger the operator, the machine qualifications are not in accordance with K3 requirements
8	Very high, 100% of the product becomes scrap, loses its main function
7	High, part to scrap, items can be used but performance decreases
6	Medium, some become scrap, lose additional functions, can't be sorted
5	Low, 100% of products can be reworked
4	Very low, products can be sorted and partially reworked
3	Minor, 100% of products can be reworked, defects can be found by some customers
2	Very Minor, 100% of products can be reworked, defects can be found by a small number of customers
1	There is no defect

Event level (Occurrence) is the likelihood that the cause will occur and results in a form of failure during the product usage period. Occurrence is a rating value that is adjusted to the estimated frequency and or the cumulative number of failures that can occur. Event evaluation is done to find out how often the possibility of failure in the production process.

Table 2. Classification of Occurrence Values

Score	**Classification**	**Failure Rate**
10	Failure Rate	>= 1 out of 2
9		1 out of 3
8	Often	1 out of 8
7		1 out of 20
6	Often enough	1 out of 80
5		1 out of 400
4		1 out of 2,000
3	Often enough	1 out of 15,000
2	Very rarely	1 out of 150,000
1	Almost never	<= 1 out of 1,500,000

The detection value is associated with the current control. Detection is a measurement of the ability to control failures that can occur. Detection assessment aims to find out how likely the failure can be detected optimally.

Table 3. Classification of Detection Values

Score	**Detection**	**Criteria**
10	Almost impossible	The controller cannot detect failure (<60%)
9	Very rarely	It is very rare for a controller to detect failure (60-69%)
8	Rarely	Rarely does the controller detect failure (70-79%)
7	Very low	The possibility of the controller detecting failure is very low (80-85%)
6	Low	Low probability of controller detecting failure (85-90%)
5	Is	The likelihood of the controller is detecting a moderate failure (90-92.5%)
4	Rather high	The likelihood of the controller detecting failure is rather high (92.5-95%)
3	High	The likelihood of the controller is detecting a high failure (95-97.5%)
2	Very high	The likelihood of the controller detecting failure is very high (97.5-99.5%)
1	Almost certainly	Failures in the process cannot occur because they have been prevented through solution design (> 99.5%)

The three parameters above are identified in each case of the production process, then three variables are multiplied and produced RPN values so they can be analyzed using FMEA and determine priorities with a Risk Priority Number (RPN).

3. METHOD

The study was conducted using the dynamic system method and FMEA (Failure Mode and Effect Analysis). In identifying the risk of failure of the production system using the FMEA process, observations were only made on the ongoing production process activities. The purpose of applying this method is to minimize the possibility of defects, so that significant improvements are obtained for problems that have occurred in the company. In addition, dynamic systems are used to model risk reduction in the failure of the production process in the company.

Dynamic system is a simulation modeling methodology used to understand complex system dynamic behavior in order to analyze and solve complex problems with focus on analysis and policy design [4]. Forrester (1961) created system dynamics methodology to design enterprises by treating the time-varying (dynamic) behavior of industrial organizations. The methodology is a powerful approach to obtain insights into dynamic complexity problems [5]. It is designed for long-term, chronic, dynamic management problems. Additionally, it is the proper method to encounter the systems with dynamic and full of feedback.

Briefly, the entire process is divided into two analyzing phases, namely qualitative and quantitative. In the qualitative phase, it starts with the observation of the systems under consideration before identifying the model objectives. Then, systems approach and analysis are applied to the observed systems by selecting properly all relevant entities and variables to the objectives in order to have a simplified and well-defined system. In the next step, a causal loop diagram is developed which is then transformed into a stock and flow diagram. During the quantitative phase, the stock and flow diagram is translated to a simulation program using SD software for developing dynamic models. Once the initial models are gathered, they are iteratively verified and validated to obtain sufficient models [6].

4. CASE STUDY

In this section, through the illustration of the data set adopted from the case problem, FMEA combined with a dynamic system produces a model to reduce the risk of failure of the iron pipe production process.

4.1 Problem

This case originated from BPI Manufacturing, located in Bekasi, Indonesia. This company produces various types of iron pipes. The company's problem now is that there are still many defective products found in the production process, where in 2018 the company's product defects are 10%, and in 2019 defective products increase to 15%.

4.2 Identification of production defects with FMEA

The BPI Manufacturing pipeline production process uses many machines and instruments that require a high level of accuracy so that the production results are in accordance with the expected specifications.

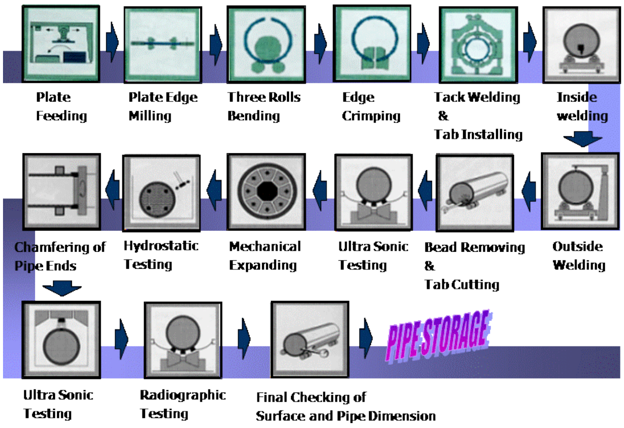


Fig. 1. The process of manufacturing BPI iron pipes

Based on the identification and direct observation in the production area, it is clear that there are factors that can still be obstacles that can reduce the level of production quality, so it needs control and caution in overcoming existing problems.

The RPN value from the FMEA results becomes a reference in the dynamic system simulation of the risk of production process failure. The number and category of defects needed in the process of making a model to accommodate the types of defects in each process are shown. The number and type of defects in the iron pipe production process are also shown in Table 6. From this table, it can be seen that the defects due to cracking/rupture resulted from the welding process is the highest with the percentage with a value of 50% of the total defects.

4.3 Modeling with Dynamic Systems

Physical flow describes the process of making a model [7]. Raw materials arrive from the Raw Materials warehouse which are then inspected. After inspection, the goods are sent to the production process by material handling. The production process is carried out and in each process, there is an inspection of each until the production process is complete and ready to be sent to the warehouse of finished goods with material handling.

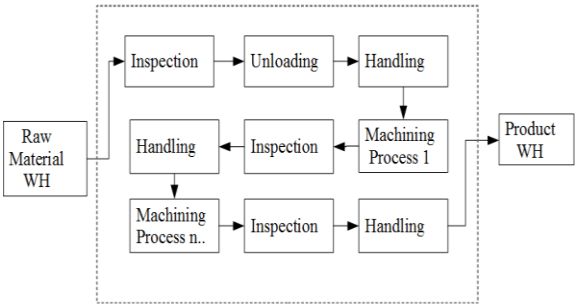
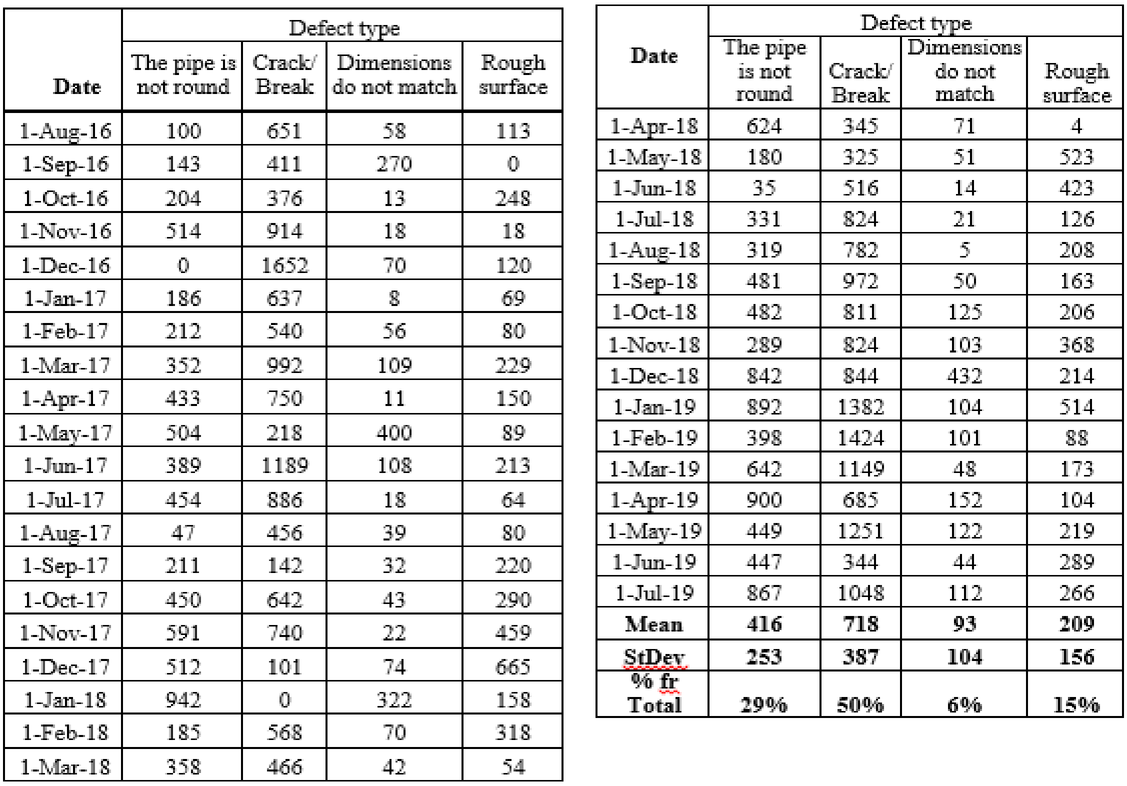


Fig. 2. Physical flow of products in the production process

Table 4. FMEA Manufacturing Process of BPI Manufacturing

No	Category	Description	Potential Failure Effects	SEV	Potential Cause	OCC	Current Control	DET	RPN
1	Production Process 1	*Rolls Bending*. Bending and rolling do not meet specifications. Roll is reduced function	The surface of the pipe is rough and not round	8	Man: not careful Machine: roll has been used for a long time	3	The process is overseen by the coordinator / supervisor, preparing a roll backup	4	96
2	Production Process 2	*Welding*. Welding results cracked/broken, rough surface. Did not pass the Ultrasonic Testing test.	Re-Work or become scrap. Poor welding, moist fluxes, unbalanced voltage and strong currents	8	Man: Cleaning isn't good, pre-heat isn't enough. Material: The arc/strip is stored for too long in storage	8	Checking tools and equipment used by operators and workers is monitored by supervisors	6	384
3	Production Process 3	*Bead Removing & Tab Cutting*. Rough surface, dimensions not suitable	Re-cutting is done	8	Man: not careful	3	The process is supervised by a coordinator/ supervisor	4	96
4	Production Process 3	*Mechanical Expanding*. Dimensions do not match	Product Reject or converted	8	Man: not careful	4	The process is supervised by a coordinator/ supervisor	2	64
Average									160

Table 5. Number and Type of Defects in BPI Manufacturing Pipe Production



Date	Defect type			
	The pipe is not round	Crack/ Break	Dimensions do not match	Rough surface
1-Aug-16	100	651	58	113
1-Sep-16	143	411	270	0
1-Oct-16	204	376	13	248
1-Nov-16	514	914	18	18
1-Dec-16	0	1652	70	120
1-Jan-17	186	637	8	69
1-Feb-17	212	540	56	80
1-Mar-17	352	992	109	229
1-Apr-17	433	750	11	150
1-May-17	504	218	400	89
1-Jun-17	389	1189	108	213
1-Jul-17	454	886	18	64
1-Aug-17	47	456	39	80
1-Sep-17	211	142	32	220
1-Oct-17	450	642	43	290
1-Nov-17	591	740	22	459
1-Dec-17	512	101	74	665
1-Jan-18	942	0	322	158
1-Feb-18	185	568	70	318
1-Mar-18	358	466	42	54
1-Apr-18	624	345	71	4
1-May-18	180	325	51	523
1-Jun-18	35	516	14	423
1-Jul-18	331	824	21	126
1-Aug-18	319	782	5	208
1-Sep-18	481	972	50	163
1-Oct-18	482	811	125	206
1-Nov-18	289	824	103	368
1-Dec-18	842	844	432	214
1-Jan-19	892	1382	104	514
1-Feb-19	398	1424	101	88
1-Mar-19	642	1149	48	173
1-Apr-19	900	685	152	104
1-May-19	449	1251	122	219
1-Jun-19	447	344	44	289
1-Jul-19	867	1048	112	266
Mean	**416**	**718**	**93**	**209**
StDev	**253**	**387**	**104**	**156**
% fr Total	**29%**	**50%**	**6%**	**15%**

The development of dynamic models in this study uses a Dynamic Systems approach. Dynamic systems are methods for enhancing learning in complex systems [8]. The Dynamic System methodology building consists of three traditional managerial disciplinary backgrounds, cybernetics, and computer simulation. The principles and concepts of these three disciplines work together by setting aside their weaknesses in solving managerial problems holistically [1].

5. RESULT AND DISCUSSION

5.1 CLD identifies the risk of the production process

Dynamic conditions that cause a risk of continuous failure in the production process can be illustrated by the relationship of variables in the production process which is a system of interrelationships between variables in the form of a variable relationship diagram (Causal Loop Diagram). CLD identifies the risk of the production process in Figure 3.

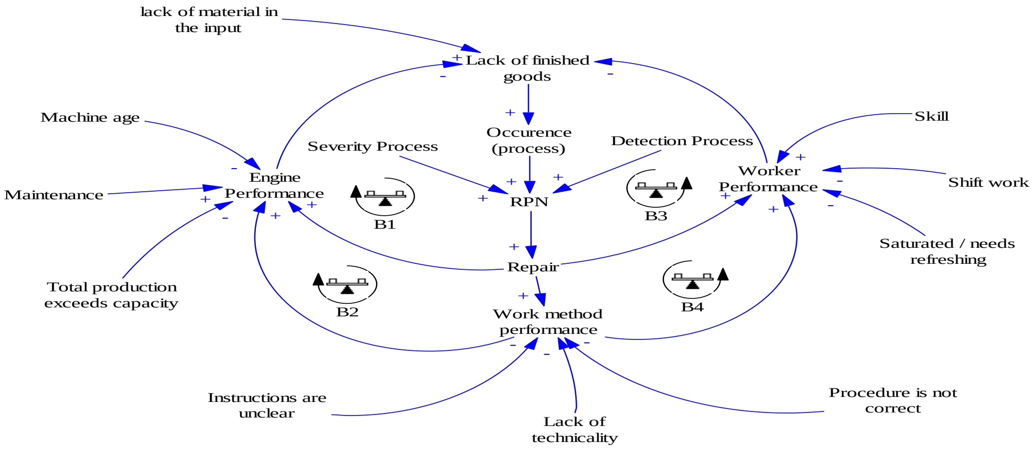


Fig. 3. CLD identifies the risk of the production process

In the production process identification system, the first loop of low engine performance (-) will increase the shortage of finished goods (+) and will also increase the value of Occurrence (+), along with severity and detection parameters, a high RPN (+) will be obtained so that priority for improvements to the system can be done by increasing engine performance, and so on for the next loop.

CLD (causal loop diagram) is translated into the structure of the SFD (stock flow diagram) flow diagram to carry out the stages of the formulation of the model.

5.2 SFD risks failure of the production process

SFD is a central concept in Dynamic Systems theory. Stock is the accumulation or collection and characteristics of system conditions and information producers, which form the basis of actions and decisions. Stocks are combined with rate or flow as information flow, so that stock becomes a source of dynamic imbalance in the system (Sterman, 2000). Model formulation is the process of translating the concept of a qualitative model into a quantitative model. The simulation model in order to run must be complete with correct mathematical equations, parameters and determination of the initial value conditions into the SFD. SFD dynamic model of the risk of failure of the production process is presented in Figure 4.

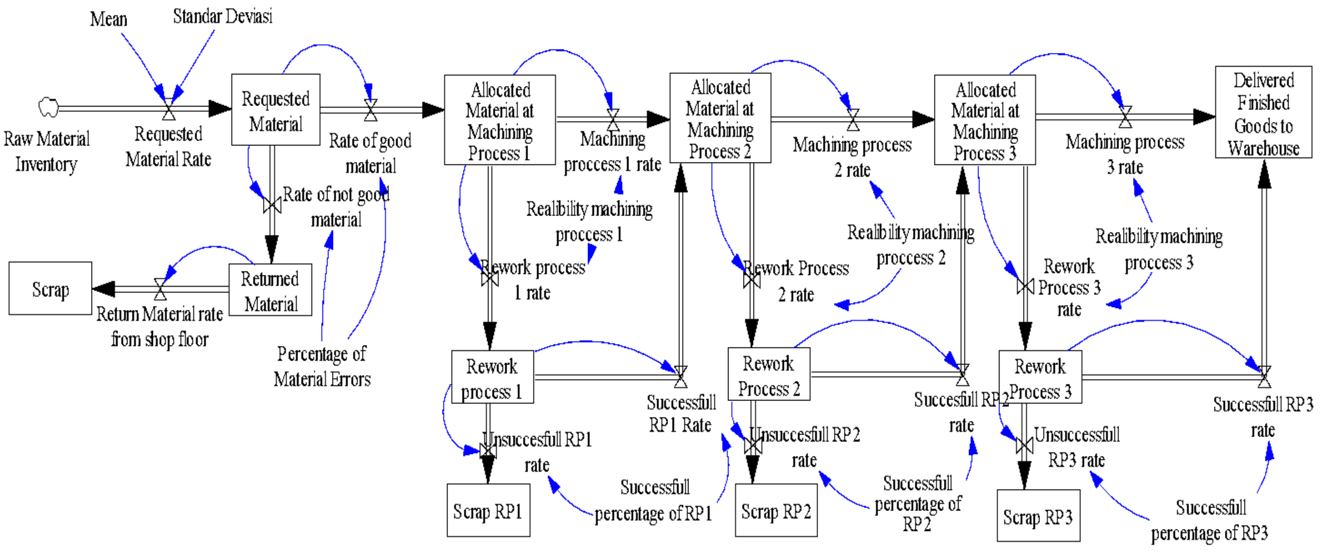


Fig. 4. SFD risks failure of the production process

To run the simulation model, a strategy to manage the risk of failure of the production process is prepared by involving exogenous variables according to Table 6. The basis for this determination is based on the results of the FMEA analysis, discussions with experts in the field and historical data on pipe manufacturing companies as research objects.

Table 6. Exogenous variables on SFD risk of failure of the production process

<table>
<tr><th>No.</th><th>Description</th><th>Scenario Category</th><th>Information</th></tr>
<tr><td>1</td><td>Reliability Machine Process</td><td><table><tr><td>Actual</td><td>Optimistic</td></tr><tr><td>Process 1 : 97%
Process 2 : 94%
Process 3 : 99%</td><td>All Process 100%</td></tr><tr><td>Moderate</td><td>Pessimistic</td></tr><tr><td>All Process 90%</td><td>All Process 80%</td></tr></table></td><td>The object of research is the range of risk that is optimistic, moderate and pessimistic according to the company's past data</td></tr>
<tr><td>2</td><td>Percentage of success Rework</td><td>Process 1 : 68%
Process 2 : 70%
Process 3 : 71%</td><td>In accordance with the average historical successful rework of the company</td></tr>
<tr><td>3</td><td>Mean</td><td>14.749</td><td>As per the historical average production of the company</td></tr>
<tr><td>4</td><td>Standard Deviation</td><td>4.217</td><td>As per the historical deviation of the company's production</td></tr>
</table>

5.3 Production Input Data Normality Test

Production input data is used as the main input during simulation, where the data must have a data pattern that can be a reference in the simulation process. If the data is very random, it is very likely that the results of the simulation validation will not be valid. Normality test is done to test whether the data pattern is normally distributed or not. The normality test is carried out with the help of Minitab software with the Anderson Darling test method. The results of the normality test of company data that are the object of research are illustrated in Figure 5.

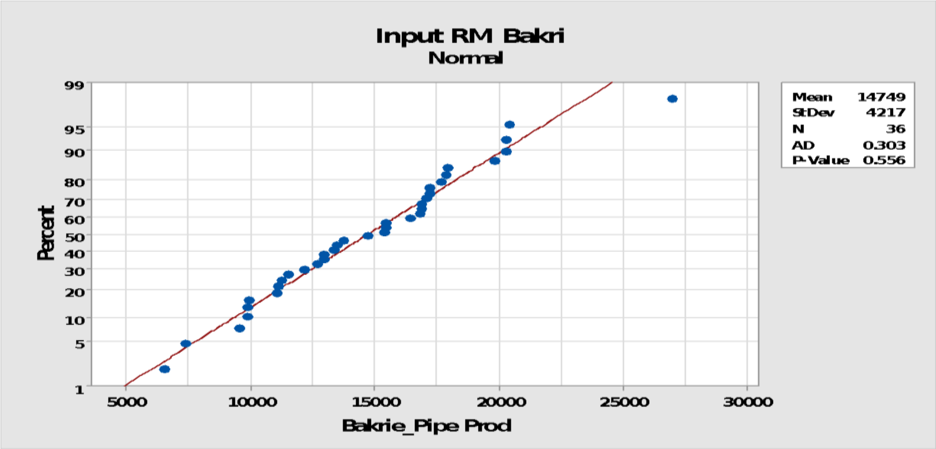


Fig. 5. Production Input Normality Test

5.4 Verification and Model Validation

Verification aims to prove whether the models that have been made are correct. In this case, the verification technique used compares the results of simulations with manual calculations. We can see from the units and formulations whether they are in accordance with what is desired or not.

The purpose of testing is to compare the simulation behavior of the model to the actual behavior of the system. In the testing phase, the modeler must ensure that the model has a "consistency dimension" in the relationship between level, rate and auxiliary units of variables and the constants must make sense. (Sterman, 2000).

Validation aims to see whether the output of the model created is in accordance with the desired goals and the real system. Data validation can be determined using two testing methods (Barlas & Wu, 1989).

a. Mean Comparison, comparing simulation results with actual data, the model is declared valid if E1 <5%.

$$E1 = \frac{|Simulation - Actual|}{Actual} \qquad (1)$$

b. % error variance, where the model will be said to be valid if E2 <30%.

$$E2 = \frac{|StDev\ Simulation - StDev\ Actual|}{StDev\ Actual} \qquad (2)$$

The results of the simulation validation are in Table 7.

Table 7. Model validation results

Month	**Raw Material**		**Delivered FG to WH**	
	Actual	**Simulation**	**Actual**	**Simulation**
Aug-16	20,285	13,416	19,738	14,276
Sep-16	11,156	12,883	10,640	13,522
Oct-16	15,376	20,709	14,820	13,712
Nov-16	17,243	13,330	16,420	14,267
Dec-16	20,317	20,747	19,309	13,099
Jan-17	13,745	15,699	13,180	12,531
Feb-17	15,446	17,905	14,827	19,559
Mar-17	17,975	13,247	17,100	13,412
Apr-17	12,194	19,520	11,381	19,631
May-17	11,532	14,823	10,895	15,553
Jun-17	26,985	16,782	25,930	17,222
Jul-17	17,114	14,187	16,400	13,156
Aug-17	7,442	10,866	7,000	18,514
Sep-17	9,900	12,132	9,366	14,681
Oct-17	12,738	8,212	12,134	16,149
Nov-17	13,378	10,173	12,394	13,929
Dec-17	11,265	17,458	10,466	10,764
Jan-18	16,916	15,311	16,094	11,684
Feb-18	13,526	11,778	12,903	8,225
Mar-18	19,824	15,405	19,331	9,739
Apr-18	6,557	21,431	6,017	16,439
May-18	12,997	16,375	12,464	14,983
Jun-18	16,926	9,366	16,264	11,661
Jul-18	20,452	18,386	19,834	14,700
Aug-18	11,046	13,109	10,222	20,374
Sep-18	12,997	16,205	12,287	16,211
Oct-18	14,712	10,442	13,801	9,560
Nov-18	16,427	12,138	15,740	17,234
Dec-18	17,865	11,263	16,849	13,055
Jan-19	17,687	11,957	16,484	15,514
Feb-19	9,957	12,210	9,128	10,509
Mar-19	15,468	13,524	14,369	11,665
Apr-19	9,558	18,401	8,776	10,979
May-19	16,864	20,552	16,101	11,550
Jun-19	9,865	20,920	9,322	11,823
Jul-19	17,239	11,986	16,276	13,026
Total	**530,971**	**532,845**	**504,259**	**502,905**
Min	**6,557**	**8,212**	**6,017**	**8,225**
Max	**26,985**	**21,431**	**25,930**	**20,374**
Mean	**14,749**	**14,801**	**14,007**	**13,970**
Stdev	**4,217**	**3,632**	**4,140**	**2,942**
E1		**0.35%**	**E1**	**0.27%**
E2		**13.87%**	**E2**	**28.95%**

FG is Finish Goods

5.5 Simulation of Proposed Improvement Scenarios

The failure risk scenario in the production process is based on actual data in an iron pipe manufacturing company and the identification of failures using FMEA and is represented as a quantified dynamic system model. Exogenous simulation variables are in accordance with Table 6. The proposed variables for the value of risk of production failure are process reliability with an optimistic rate of 100%, moderate 90% and pessimistic 80%. The results of the simulation for 5 years (60 months) are in Table 8 and the visualization of the simulation in Figure 6.

Table 8. Simulation results of risk of production failure

Parameter	Actual	Optimistic	Moderate	Pessimistic
Input (Ton)	14749			
Average (Ton)	14190	14633	13337	12120
St Dev	3302	3606	2801	2269
Difference from actual	-	443	-854	-2070
% Success	96%	99%	90%	82%
Rank	2	1	3	4

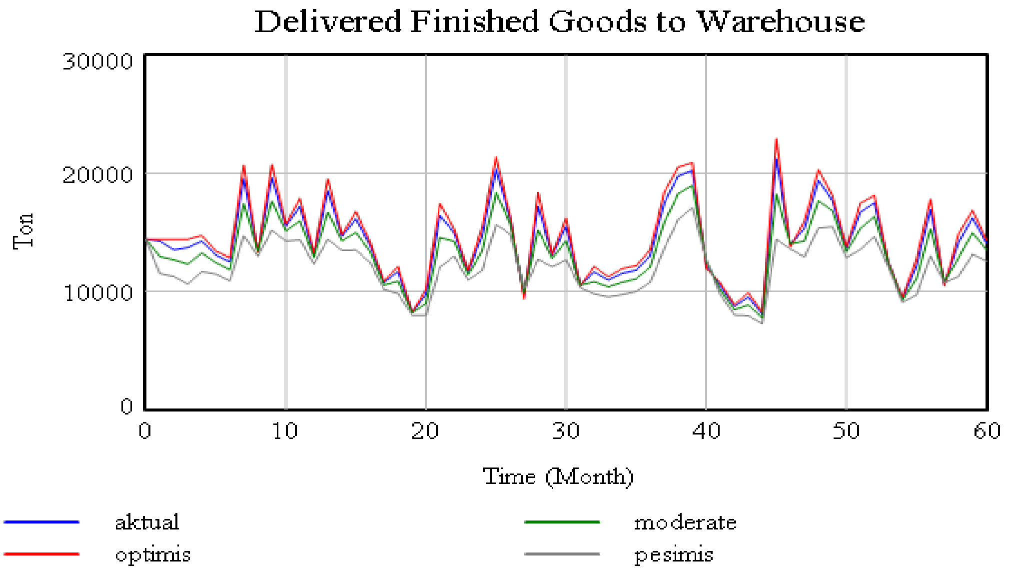


Fig. 6. Simulation results of all risk scenarios of production failure

The output of this simulation is to compare the risk of production process failure in several scenarios. The best scenario results are shown in an optimistic scenario with 100% process reliability with 99% production process success. If the selling price of materials at BPI Manufacturing is IDR 17,000,000/ton, then for an optimistic scenario which has a difference of 443 tons from the actual, the company can make savings of IDR 7,531,000,000 per month.

6. CONCLUSION

The dynamic system model developed describes the risk conditions of the failure of the production process. The designed model has validated the actual results that did not differ significantly from the simulation results. The risk of failure in the production process is based on expert review, actual Manufacturing BPI data, and identification of failure using FMEA which is then represented as a quantified dynamic system.

Several policy scenarios related to the risk of failure of the production process are tested to get a percentage of production success each month. Exogenous variables from this simulation are the reliability of the machine process and the percentage of rework success. Machine process reliability factor is used as an object of research with an optimistic risk range with a value of 100%, moderate with a value of 90% and pessimistic with a value of 80%.

The simulation results show that the optimistic scenario has the largest final product yield of 99%, then the actual condition is 96%, moderate is 90% and pessimistic is 82%. The optimistic situation has a difference of 443 tons from its actual condition, so the company can make savings of IDR 7,531,000,000 per month.

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