Monitoring Welding Process on Ship Construction Using Demerit Control Chart and Fuzzy Analytics Hierarchy Process Integrated Statistical Process Control

Muhammad Ahsan, Bunga Tata Arinda, and Ichwanul Kahfi Prasetya

***Abstract*: Quality monitoring in the welding process of ship construction has been carried out using a rejection ratio. However, this approach is ambiguous and does not provide a clear indication of whether the welding process is under control. Statistical quality control (SQC) is a more effective method of quality monitoring that can provide a more definitive assessment of the welding process. In this paper, we propose a new SQC method for the welding process based on the demerit chart. The demerit chart is a statistical tool that uses a weighted sum of defect sizes to assess the quality of a product. We have developed a new demerit chart that is based on the analytic hierarchy process (AHP), a decision-making method that can be used to assign weights to different factors. We evaluated the performance of our new demerit chart using data from a ship construction project. The results showed that our demerit chart was able to detect welding defects that were not detected by the rejection ratio method. We also found that our demerit chart was more sensitive to changes in the welding process than the rejection ratio method. Our results suggest that the demerit chart is a more effective method of quality control for the welding process than the rejection ratio method. The demerit chart is capable of detecting welding defects that are not detected by the rejection ratio method, and it is more sensitive to changes in the welding process.**

***Index Terms*—PCA. AHP, Control Chart, Demerit, Fuzzy AHP, Welding**

I. Introduction

The shipbuilding industry is a key part of the maritime industry, which is essential to connect regions through sea transportation. Ships are often constructed using a block system, which involves welding. However, welds often do not meet predetermined criteria. Therefore, welding inspections are necessary to maintain the quality of the product. Weld inspections on ships are conducted using radiographic testing (RT), which shows defects in the welds on the film. To date, the quality of the welding process has been monitored using a rejection ratio, which compares the size of each type of defect with the overall length of the weld. The production department uses the results of quality monitoring to improve the welding process. However, this approach does not provide a clear indication of whether the welding process is under control. Therefore, statistical quality control (SQC) is necessary.

Companies use quality control in their production processes to ensure that the products or services they produce meet the company's expectations and standards. Statistical quality control (SQC) is a set of techniques that use statistical methods to monitor and control the quality of products or services. SQC techniques can be used to identify potential problems in the production process, prevent defects from occurring, and improve the overall quality of products or services produced [1]. One of the statistical methods that are often used in quality control is the control chart. In this case, there are two types of control charts, namely variable [2]–[4] and attribute [5]–[8] control charts. The variable control chart is used for measurable quality characteristics, while the attribute control chart is used to classify quality characteristics into defective or non-defective categories [9].

Statistical quality control for RT inspection data on ship X is best conducted using a u-chart. This is because the inspection process involves counting the number of defects, as well as the types of defects that are present. However, each type of defect has a different level of severity, so a demerit control chart would be more appropriate for this incident. The weights for each category of defects are determined independently and are limited, which can provide limited information and lead to bias [10]. Thus, fuzzy sets theory seems logical to overcome subjectivity in determining weights.

The Analytical Hierarchy Process (AHP). is a multi-criterion decision making (MCDM) technique that can be used to determine the weights of criteria. The AHP method is based on the principle of pairwise comparisons, in which each criterion is compared with every other criterion. The results of these pairwise comparisons are then used to calculate the weights of the criteria. The AHP method has been criticized for being too subjective. This is because the weights of the criteria are determined by the preferences of the decision-makers. In order to address this issue, a fuzzy set technique has been developed called Fuzzy AHP. Fuzzy

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AHP allows for the inclusion of uncertainty in the decision-making process. This makes it more suitable for situations where there is a lack of consensus among the decision-makers. The combination of the AHP method with the fuzzy approach has been shown to be more effective than either method alone in dealing with subjective decision making. This is because fuzzy AHP allows for the inclusion of uncertainty in the decision-making process, while the AHP method provides a structured framework for making decisions [11].

In a previous study, Sagnak and Kazancoglu [10] integrated a fuzzy Analytical Hierarchical Process (AHP) with a demerit control chart to assess the level of disability using linguistic variables. The main difference between a demerit control chart and a FAHP demerit control chart is how demerit weights are allocated. In a demerit control chart, the weighting scheme is typically standard and constant, which may not reflect the company's actual assessment of the production process. FAHP can be used to incorporate the company's assessment into the demerit control chart, which can lead to more accurate defect weights [10].

Statistical quality control (SQC) of the welding process is necessary to determine whether the welding process is statistically controlled. SQC is performed using four types of control charts: u control charts, demerit control charts, AHP demerit control charts, and fuzzy AHP demerit control charts. The fuzzy membership function used in this control chart is triangular. The results of the decisions of the four control charts are then compared to determine the sensitivity of each control chart. Furthermore, in this study, a process capability analysis was also carried out to determine whether the welding process was capable or not.

II. LITERATURE REVIEW

A. Demerit Control Chart

An attribute control chart is a control chart used on quality characteristics that cannot be measured and only provides a decision in the form of a statement of acceptance or rejection [1]. *The U* control chart measures the number of defects from each unit with more than one quality characteristic and a constant or a different number of samples. *The U* control chart is based on the average number of defects per unit [12], which can be calculated using (1).

$$u_i = \frac{x_i}{n_i} \tag{1}$$

The average number of defects per unit ($\bar{u}$) is used as the center line with a control limit of the *U* chart. The demerit control chart measures the number of defects in each unit by categorizing them according to their seriousness [1]. The number of weighted defects in each subgroup is shown by (2) [13].

$$D_i = w_1 d_{i1} + w_2 d_{i2} + w_3 d_{i3} + w_4 d_{i4} \tag{2}$$

where $i = 1, 2, \ldots, r$.

The average number of defects per unit (u_i) for r subgroups of observations is obtained by (3) and then calculated by the average number of defects per unit overall ($\bar{U}$) using (4).

$$u_i = \frac{D_i}{n_i} \tag{3}$$

$$\bar{U} = w_1\bar{u}_1 + w_2\bar{u}_2 + w_3\bar{u}_3 + w_4\bar{u}_4 \tag{4}$$

$\bar{U}$ is used as the center line with a control limit of $\bar{u} \pm 3\hat{\sigma}_u$ which $\hat{\sigma}_u$ is obtained by (5).

$$\hat{\sigma}_u = \sqrt{\frac{w_1^2\bar{u}_1 + w_2^2\bar{u}_2 + w_3^2\bar{u}_3 + w_4^2\bar{u}_4}{n_i}} \tag{5}$$

B. Analytical Hierarchy Process (AHP)

The analytic hierarchy process (AHP) is a multi-criteria decision-making (MCDM) method that can be used to solve complex problems. AHP breaks down a problem into a hierarchy of criteria and then uses pairwise comparisons to assign weights to each criterion. The weights are then used to calculate a priority score for each alternative solution. The numerical value is obtained from the rating scale determined by Saaty [14] in Table I.

Furthermore, calculating the geometric mean on several assessments is carried out using Equation (6). This calculation is done to better approximate the average.

TABLE I
IMPORTANCE'S DEGREE OF PAIRWISE COMPARISONS

Degree of Importance	Definition
1	Equally important
3	One element is slightly more important than the other
5	One element is more important than the other
7	One element is clearly more important than the other
9	One element is absolute important than the other
2,4,6,8	The value that lies between two adjacent comparisons

$$G = \sqrt[y]{q_1 \cdot q_2 \cdot q_3 \cdot \ldots \cdot q_y} \tag{6}$$

where q is the result of the response's assessment and y is the number of respondents.

Meanwhile, the table of the pairwise comparison matrix is shown in Table II.

where K is the criterion as a basis for comparison and K_1, K_2, …, K_n are some of the elements below it. After compiling the pairwise comparison matrix, the next step is to normalize the pairwise comparison matrix and determine the weight of the criteria by calculating the average of each row of the normalized matrix as (7).

TABLE II
PAIRWISE COMPARISONS MATRIX

K	K_1	K_2	…	K_N
K_1	I	p_{12}	…	p_{1n}
K_2	p_{21}	I	…	P_{2n}
…	…	…	…	…
K_n	p_{n1}	p_{n2}	…	I

$$W_c = \frac{\sum_{i=1}^{m} p_{ij}}{m} \tag{7}$$

The AHP analysis is said to be valid if the results are consistent. The Consistency Ratio (CR) value is calculated using (8) [15], where RI is the Random Index, and CI is the Consistency Index obtained by (9). The RI value has been formulated by Saaty as shown in Table III.

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{8}$$

$$\mathrm{CI} = \frac{\lambda_{\max} - n}{n-1} \tag{9}$$

TABLE III
RANDOM INDEX SCORE

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

The AHP analysis can be consistent if the CR value is less than 10% [10].

C. *Fuzzy logic*

Fuzzy set theory is an extension of classical set theory (crisp), which Zadeh developed in 1965 [16]. Fuzzy logic recognizes only two states but also several states in the interval [0,1]. The main component of fuzzy set theory is the membership function. Several types of fuzzy membership functions include linear representation, triangular curve representation, trapezoidal curve representation, and shoulder shape curve representation [17].

A triangular fuzzy number (TFN) is used to determine the degree of fuzzy membership of AHP, which is formed from a combination of two lines (linear) as shown in Figure 2, and the membership function of TFN is shown by (10) [18].

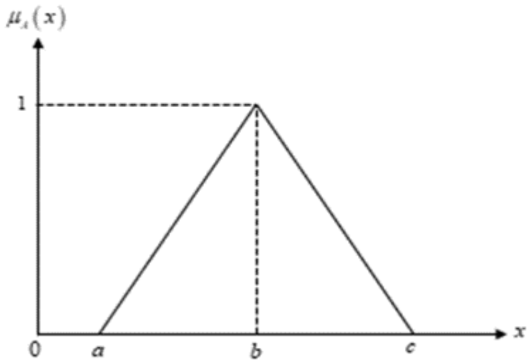

Fig. 1. Triangular Fuzzy Number

$$\mu_A(v) = \mu = \begin{cases} \dfrac{v-a}{b-a}, & a \le v \le b \\ \dfrac{c-v}{c-b}, & b \le v \le c \\ 0, & \text{others} \end{cases} \tag{10}$$

D. *Fuzzy Analytical Hierarchy Process (Fuzzy-AHP)*

Fuzzy AHP is the development of the traditional AHP method carried out by Chang. It represents the importance scale of each element contained in the pairwise comparison matrix using triangular fuzzy numbers (TFN). This number is symbolized by $M = (a, b, c)$ where $a \le b \le c$ and a is low, b is medium, and c is high [19]. The application of TFN is shown in Table IV, where decision makers use the numbers to express experts' preferences when comparing elements.

TABLE IV
FUZZIFICATION SCALE OF PAIRWISE COMPARISONS

Lingusitic Variables	Fuzzy Number Scale	Reciprocal Fuzzy Number Scale
Equally important (SP)	(1, 1, 1)	(1/1, 1/1, 1/1)
Equally to moderately more important	(1, 2, 3)	(1/3. 1/2, 1/1)
Moderately more important (SLP)	(2, 3, 4)	(1/4, 1/3, 1/2)
Moderately to strongly more important	(3, 4, 5)	(1/5, 1/4, 1/3)
Strongly more important (LP)	(4, 5, 6)	(1/6, 1/5, 1/4)
Strongly to very strongly more important	(5, 6, 7)	(1/7, 1/6, 1/5)
Very strongly more important (JSP)	(6, 7, 8)	(1/8, 1/7, 1/6)
Very strongly to extremely more important	(7, 8, 9)	(1/9, 1/8, 1/7)
Extremely more important (MSP)	(8, 9, 9)	(1/9, 1/9, 1/8)

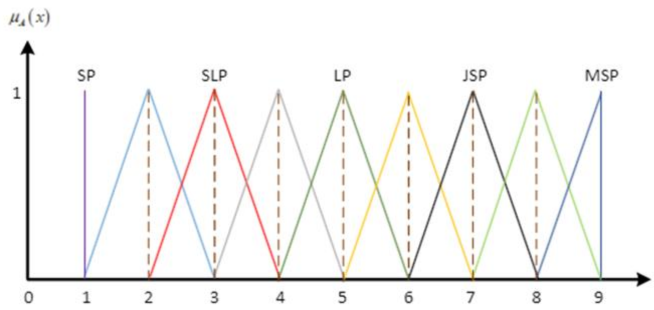

Fig. 2. Fuzzification Scale Graph

The Fuzzification scale of the pairwise comparison from Table IV can be described in Figure 2. Fuzzy weights are determined using a scale of importance (Table 1) and converted into fuzzy numbers (Table IV). The geometric mean is then calculated, followed by the definition of fuzzy synthetic extents using (11).

$$S_i = \sum_{j=1}^{m} M_{g_i}^{j} \otimes \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^{j} \right]^{-1} \tag{11}$$

where $M_{g_i}^{j}$ (j = 1, 2, …, m) is TFN. The weight value of each criterion is determined by the degree of possibility through (12) and the degree of possibility for convex fuzzy numbers that are greater than k fuzzy convex numbers defined by (13).

$$V(M_2 \ge M_1) = \begin{cases} 1, & b_2 \ge b_1 \\ 0, & a_1 \ge c_2 \\ \dfrac{(a_1 - c_2)}{(b_2 - c_2) - (b_1 - a_1)}, & \text{others} \end{cases} \tag{12}$$

$$V(M \ge M_1, M_2, \ldots, M_k) = \min\left(V(M \ge M_i)\right) \tag{13}$$

If it is assumed $d'(A_i) = \min\ V(S_i \ge S_k)$ for k=1,2,…,n and $k \ne i$, then the vector weight is given by the value of

W' which is normalized to $W = \left(d\left(A_1\right), d\left(A_2\right), \ldots, d\left(A_n\right)\right)^T$.

E. Welding Process on Ship

Ship construction uses a block system that includes fabrication, subassembly, assembly, Block Blasting Shop (BBS), grand assembly, and erection. The welding process is essential to join the completed blocks. Welding is a method of joining two solid metal pieces by melting them through heat [20].

Non-destructive testing (NDT) can be used to inspect welding processes. Radiographic testing (RT) is an NDT method that uses X-rays to penetrate objects and create images of internal defects, such as cracks, incomplete penetration (IP), incomplete fusion (IF), slag inclusions (SI), and porosity. These defect types are illustrated in Figure 4.

TABLE V
RESEARCH VARIABLES

Defect Class	Defect Weight	Variables	Defect Type
A (Very Seious)	100	X_1	Crack
B (Serious)	90	X_2	Incomplete Penetration
		X_3	Incomplete Fusion
C (Moderately Serious)	60	X_4	Slag Inclusion
D (Almost Serious)	50	X_5	Porosity

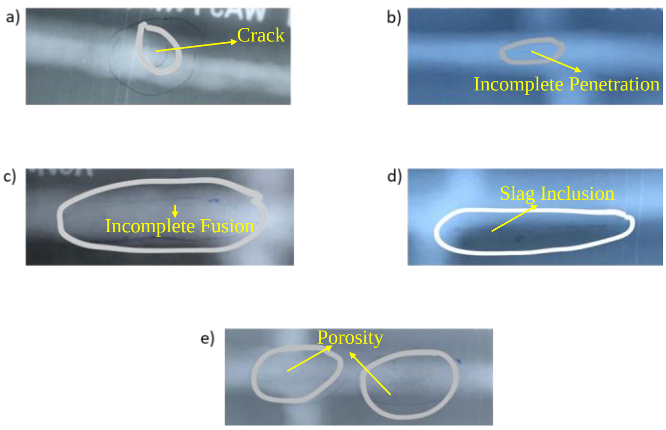

Fig. 3. Defect type: a) Crack, b) Incomplete Penetration, c) Incomplete Fusion, d) Slag Inclusion, and e) Porosity

III. METHODOLOGY

A. Data Source and Structure

The data used in this study were collected by the Quality Assurance Division from January 2020 to June 2021. It includes the results of radiographic testing (RT) inspections of the welding process during the construction of ship X. The data structure is shown in Table VI.

B. Analysis Steps

The steps taken in this research are as follows:

1. Formulating research problems and objectives.
2. Collecting data from welding defect inspection.
3. Data exploration of welding defect inspection using descriptive statistics.
4. Determining the most dominant type of defect in welding defect inspection data using a Pareto chart.
5. Building the control chart u with the following steps:
   a. Calculating the average defect per unit.

TABLE VI
DATA STRUCTURE

Subgroup	Sample	A	B	C	D
1	n_1	C_{1a}	C_{1b}	C_{1c}	C_{1d}
2	n_2	C_{2a}	C_{2b}	C_{2c}	C_{2d}
3	n_3	C_{3a}	C_{3b}	C_{3c}	C_{3d}
⋮	⋮	⋮	⋮	⋮	⋮
m	n_m	C_{ma}	C_{mb}	C_{mc}	C_{md}

   b. Calculating the upper and lower control limits and the center line on the u control chart.
   c. Building u control chart.
6. Building a Demerit Control Chart with the following steps:
   a. Identify and divide the defect categories of the welding defect inspection data by the company's expert provisions.
   b. Giving weight to welding defect inspection data for each category of defects according to their severity.
   c. Counting the number of weighted defects for each class.
   d. Counting the number of weighted defects in each subgroup.
   e. Calculating the average defect per unit.
   f. Calculating the average number of defects per unit.
   g. Calculating the upper and lower control limits and the center line on the demerit control chart.
   h. Building a demerit control chart.
7. Building an AHP demerit control chart with the following steps:
   a. Identify and divide the defect categories of the welding defect inspection data by the company's expert provisions.
   b. Creating a pairwise comparison matrix from the expert's decision on the importance of the defect category in the welding defect inspection data.
   c. Normalizing the data in the pairwise comparison matrix by dividing the value of each element in the pairwise comparison matrix by the total value of each column.
   d. Determining the score or weight for each category of defects by calculating the average of each row of the normalized pairwise comparison matrix.
   e. Calculating the Consistency Ratio (CR) value. The results of the AHP analysis are said to be consistent if the CR value is less than 10%.
   f. Calculate the upper and lower control limits and the center line on the demerit control chart based on the weighting results of each category in step d.
   g. Building AHP demerit control chart.
8. Building a fuzzy AHP demerit control chart with the following steps:
   a. Identify and divide the defect categories of the welding defect inspection data by the company's expert provisions.
   b. Creating a pairwise comparison matrix from the

expert's decision on the importance of the defect category in the welding defect inspection data.
c. Performing fuzzy number transformation on pairwise comparison matrix.
d. Evaluating the importance of defect categories in welding defect inspection data.
e. Calculating the weights for each category of defects in the welding defect inspection data using fuzzy AHP.
f. Calculate the upper and lower control limits and the center line on the demerit control chart based on the weighting results of each category.
g. Building a fuzzy AHP demerit control chart.

9. Comparing the results obtained in the control chart of u, demerit, AHP demerit, and fuzzy AHP demerit.
10. Conducting capability process analysis.
11. Conclusions and suggestions.

IV. Result and Analysis

A. Quality Control of Welding Process Using U Control Chart

The Pareto chart in Figure 5 shows that porosity and inclusion of slag are the most common types of welding defects, accounting for 33.3% of all defects. The other three categories of welding defects each account for 11.1% of defects. The *U* control chart is a statistical tool that can be used to monitor the number of defects in each unit of a product. It can be used with a constant or variable sample size. Figure 6 shows the results of a quality control analysis of the welding process using the *U* control chart. The graph shows that all observation points are within the control limits, indicating that the welding defect inspection results are statistically controlled.

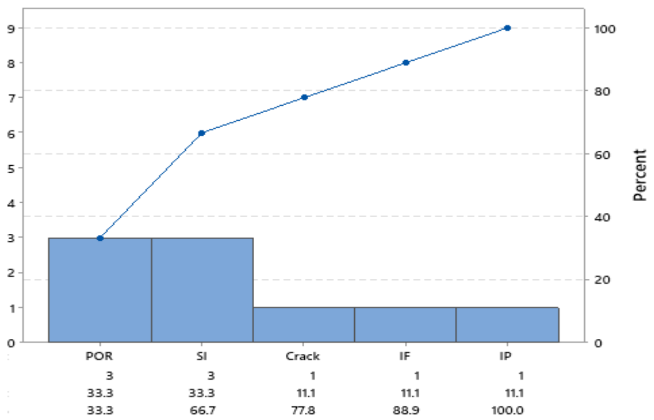

Fig. 5. Pareto Chart of Welding Defects

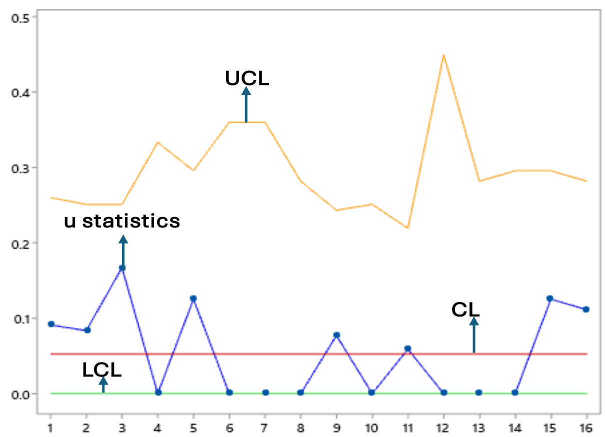

Fig. 6. *u* Control Chart

TABLE VII

$\overline{u}$ Value for Each Class of Defects

Descriptions	Score
$\overline{u}_A$	0.005
$\overline{u}_B$	0.009
$\overline{u}_C$	0.021
$\overline{u}_D$	0.017

B. Quality Control of Welding Process Using Demerit Control Chart

The demerit control chart is a statistical tool used to monitor the quality of welded products. It does this by assigning a weight to each type of defect based on its severity. The weights are shown in Table V. The average number of defects per unit is calculated for each subgroup of observations, and these values are used to calculate the center line (CL) and the control limits on the demerit control chart. Figure 7 shows the results of a analysis of the demerit control graph of the welding process. The chart shows that all observation points are within the control limits, indicating that the welding process is statistically controlled.

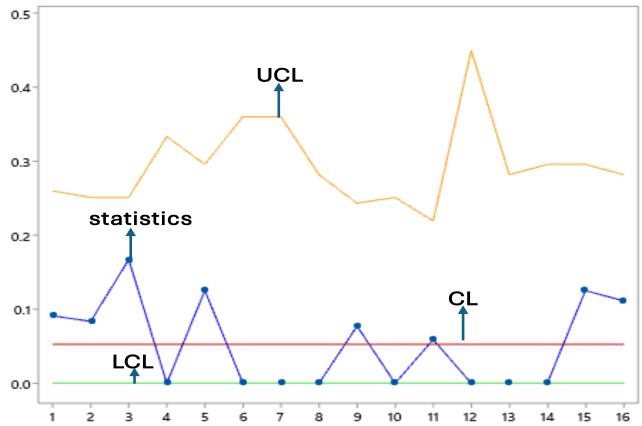

Fig. 7. Demerit Control Chart

C. Quality Control of Welding Process Using An AHP Demerit Control Chart

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The analytical hierarchy process (AHP) is a decision-making method that can be used to make decisions that involve multiple criteria and subjective judgments. In this case, four company experts used AHP to assess the severity of welding defects. They first created a pairwise comparison

TABLE VIII
PAIRWISE COMPARISONS MATRIX

	Class A	Class B	Class C	Class D
Class A	1.000	3.663	9.000	7.172
Class B	0.273	1.000	7.113	6.435
Class C	0.111	0.141	1.000	1.778
Class D	0.139	0.155	0.562	1.000

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TABLE IX
NORMALIZED PAIRWISE COMPARISONS MATRIX

	Class A	Class B	Class C	Class D
Class A	0.656	0.739	0.509	0.438
Class B	0.179	0.202	0.402	0.393
Class C	0.073	0.028	0.057	0.109
Class D	0.092	0.031	0.032	0.061

matrix which showed how they compared each defect with each other defect. The geometric mean of the pairwise comparison matrix is shown in Table VIII. The normalization of the pairwise comparison matrix is shown in Table IX.

The relative importance of each class of defects is determined by averaging the rows of the normalized pairwise comparison matrix. The results of this calculation are shown in Table X. The AHP analysis resulted in a consistency ratio (CR) of 0.088, indicating that the calculation of the defect weights is consistent. The consequences are then used to calculate the number of weighted defects and the average number of defects per unit for each subgroup of observations. The values obtained for each class of defects are shown in Table XI.

TABLE X
WEIGHT OF EACH CLASS OF DEFECTS

Defect Class	Weight Score
A	0.585
B	0.294
C	0.067
D	0.054

TABLE XI
$\overline{u}$ VALUE FOR EACH CLASS OF DEFECTS

Descriptions	Score
$\bar{u}_A$	0.005
$\bar{u}_B$	0.009
$\bar{u}_C$	0.021
$\bar{u}_D$	0.017

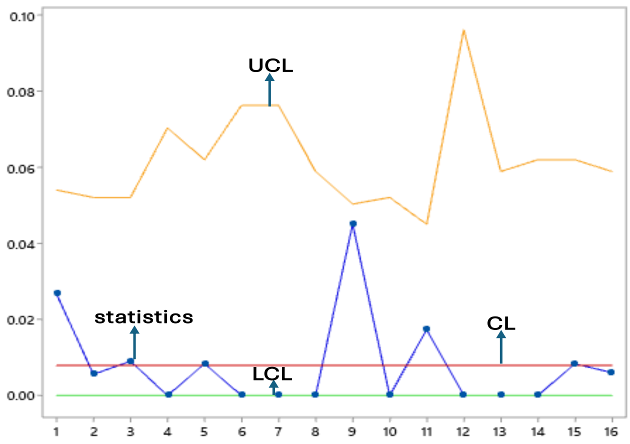

Fig. 8. AHP Demerit Control Chart

The values obtained from the analysis are used to calculate the center line (CL) and control limits for a demerit control chart. The results of the quality control analysis of the welding process using the demerit control chart are shown in Figure 8. The AHP demerit control chart was able to identify an anomaly at the 9th observation point. However, the point was still below the control limit, which indicates that the welding defect inspection results are statistically controlled.

D. Quality Control of Welding Process Using An AHP Demerit Control Chart

Fuzzy AHP is an extension of the AHP method that allows for the assessment of subjective factors, such as the severity of welding defects. This is done using fuzzy logic to represent the uncertainty in the expert judgments. The geometric mean of the pairwise comparison matrix in Table XII is used to calculate the fuzzy synthetic extent in Table XIII, which is a measure of the general importance of each class of defects. The normalized vector weight gives the relative importance of each class of defects. The results of the weight calculation are given in Table XIV.

The consistency ratio (CR) in fuzzy AHP analysis is calculated using the same method as in conventional AHP, resulting in a value of 0.088. This indicates that the weight calculation is consistent. The weights are then used to calculate the number of weighted defects and the average defects per unit for each subgroup of observations. The values obtained for each class of defects are shown in Table XV.

The values obtained from the analysis are used to calculate the center line (CL) and control limits on the demerit control chart. The results of the quality control analysis of the welding process using the demerit control chart are shown in Figure 9. The figure shows that an observation point is outside the control limits, indicating that the welding defect inspection results are not statistically controlled. The out-of-control observation point is located in the ninth sample, where a crack defect was found. Crack defects are caused by extreme temperatures at the beginning or end of the welding process and are considered severe defects that cannot be tolerated. To obtain a demerit control chart based on iteration I fuzzy AHP, the out-of-control observation points are eliminated. The results are shown in

TABLE XII
WEIGHT OF EACH DEFECT

	Class A			Class B			Class C			Class D		
Class A	1.000	1.000	1.000	3.162	3.663	4.141	8.000	9.000	9.000	9.000	7.172	7.969
Class B	0.241	0.273	0.316	1.000	1.000	1.000	6.086	7.113	8.132	5.422	6.435	7.445
Class C	0.111	0.111	0.125	0.123	0.141	0.164	1.000	1.000	1.000	1.075	1.778	2.711
Class D	0.125	0.139	0.162	0.134	0.155	0.184	0.369	0.562	0.931	1.000	1.000	1.000

TABLE XIII
FUZZY SYNTHETIC EXTENT

Defect Class	Low	Medium	High
A	0.405	0.514	0.632
B	0.282	0.366	0.483
C	0.051	0.075	0.114
D	0.036	0.046	0.065

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TABLE XIV
WEIGHT OF EACH CLASS OF DEFECTS

Defect Class	Weight Score
A	0.744
B	0.256
C	0.000
D	0.000

TABLE XV
$\overline{u}$ VALUE FOR EACH CLASS OF DEFECTS

Descriptions	Score
$\overline{u}_A$	0.005
$\overline{u}_B$	0.009
$\overline{u}_C$	0.021
$\overline{u}_D$	0.017

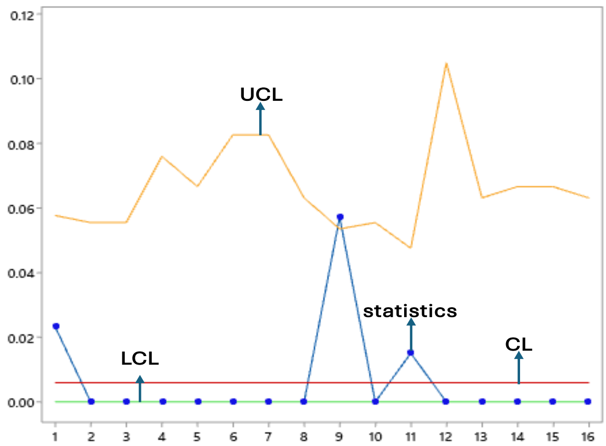

Fig. 9. Fuzzy AHP Demerit Control Chart

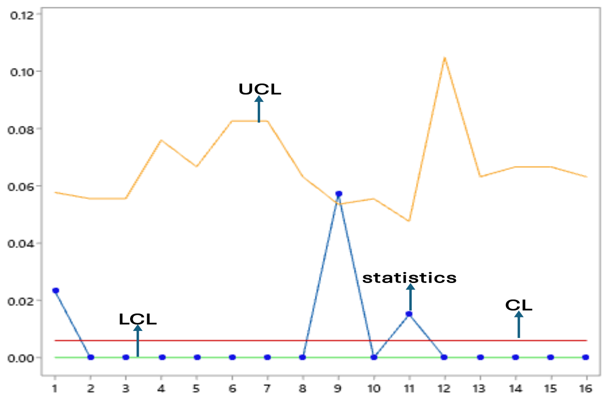

Fig. 10. Fuzzy AHP Demerit Control Chart Iteration I

Figure 10. The figure shows that, after the elimination of the out-of-control observation, there are no more out-of-control observations. This indicates that the results of the welding Based on the results, defect inspection are statistically controlled.

E. Comparisons

The effectiveness of welding process quality control using different control charts can be compared by the number of out-of-control observation points. Table XVI shows the number of out-of-control observation points for each control chart. The table shows that the fuzzy AHP demerit control chart had the fewest out-of-control observation points, indicating that it was the most effective control chart for the welding process.

TABLE XVI
NUMBER OF OUT-OF-CONTROL OBSERVATIONS

Control Chart	Number of Out of Control
u Control Chart	0
Demerit Control Chart	0
AHP Demerit Control Chart	0
Fuzzy AHP Demerit Control Chart	1

The fuzzy AHP demerit control chart was more sensitive in detecting out-of-control processes than the other control charts. The demerit control chart uses defect weights determined by a single expert, while the AHP demerit control chart uses disability weights assigned by multiple experts. Fuzzy AHP, on the other hand, considers the subjectivity of the expert assessments when determining defect weights. This makes the fuzzy AHP demerit control chart more likely to identify out-of-control processes.

TABLE XVII
WEIGHT OF EACH CLASS OF DEFECTS

Coefficient	Score
$\hat{p}$	0.003
$\hat{P}_{pk}^{\%}$	0.916

F. Capability Process Analysis

The welding process capability is assessed using capability process analysis. The results of this analysis, which are shown in Table XVII, indicate that the value is less than one. Therefore, it can be concluded that the welding process is incapable.

V. SUMMARY AND SUGGESTIONS

Analysis of the welding process used in ship construction revealed that the most common types of welding defects are porosity and inclusion of slag. Quality control using u, demerit and AHP demerit control charts showed that welding defect inspection results are statistically controlled. However, quality control using fuzzy AHP demerit control charts showed that welding defect inspection results are not statistically controlled. A comparison of quality control in the four control charts showed that the fuzzy AHP demerit control chart is more sensitive to out-of-control observation points than the other three control charts. The calculation of the performance process index ($\hat{P}_{pk}^{\%}$) yielded a value of

0.916, which indicates that the welding process used in the construction of the ship is incapable. The research findings suggest that the company should focus on reducing the occurrence of porosity defects and slag inclusion defects. This can be achieved by providing training to welders on how to minimize procedural errors that may cause these defects. Further research is needed to determine the most effective way to reduce these defects, but the average run length (ARL) method is a promising approach. Also, it is recommended to use the multivariate exponentially weighted moving average (MEWMA) [21].

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