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*Bakhshali BAKHTIYAROV* [1*], *Aynur JABIYEVA* [1], *Mahabbat KHUDAVERDIYEVA* [1]
[1] Azerbaijan State Oil and Industry University, Azerbaijan, bekhtiyarov@gmail.com, aynur.cabiyeva@asoiu.edu.az, mahabbat.xudaverdiyeva@asoiu.edu.az
[*] Corresponding author: bekhtiyarov@gmail.com

# SCADA-Driven big data framework for fault prediction in spiral steel pipe manufacturing using fuzzy and neural network models

**Abstract**

*The increasing complexity of spiral steel pipe production necessitates the implementation of intelligent forecasting methods to predict potential failures. This, in turn, enables the development of reliable evaluation techniques aimed at minimizing unanticipated breakdowns and enhancing the efficacy of maintenance strategies. In the present study, a novel SCADA-integrated framework is proposed, which incorporates Fuzzy Comprehensive Evaluation (FCE) and Artificial Neural Networks (ANN) into mid-to-long-term reliability analysis and machine learning-based short-term fault prediction. The architecture performs dynamic analysis on the health of the equipment, welding, alignment, hydraulics, and motor systems using a synthetic SCADA dataset that includes more than 100,000 time-series data points. The generation of imprecise reliability grades is predicated on essential indicators, including mean time between failures (MTBF), mean time to repair (MTTR), the level of failure, and the difficulty of its detection. These indicators are subsequently modeled through artificial neural networks (ANNs) to enable real-time inference. The multi-week sensor window and alarm logs are used with tree-based classifiers and statistical models to predict faults up to four weeks in advance. The mean prediction accuracy is over 91%, and a cost-benefit analysis indicates that active maintenance planning can result in significant financial savings. The combined use of fuzzy logic and neural networks is particularly valuable in manufacturing environments because it integrates human-like reasoning with data-driven learning, enabling robust decision-making under uncertainty. The all-inclusive solution is a financially reasonable and scalable alternative for implementing predictive diagnostics in industrial steel pipe production settings.*

## 1. INTRODUCTION

The production of spiral steel pipes is an important aspect of global infrastructure development, given the widespread use of steel pipes in the oil and gas ecosystem and water transportation systems (Shiryaev et al., 2018). Welding, forming, and inspection are the main stages of the production process, during which complex industrial systems are subjected to high thermal loads, mechanical stresses, and vibrations (Zhang et al., 2024). As automation systems become more autonomous and interconnected, the risk of failure due to sensor drift, machine degradation, or control system failures increases (Hindy et al., 2019). These failures can result in unexpected downtime, defective products, high maintenance costs, and unsafe working conditions on the factory floor.

Real-time failure prediction and reliability assessment are becoming necessary to maintain product quality and minimize operational disruptions (Lee et al., 2020). Supervisory control and data acquisition (SCADA) systems are widely used in modern manufacturing facilities to track sensor data in real time, record occasional anomalies, and track operational events (Marti-Puig & Núñez-Vilaplana, 2024). In spiral pipe production lines, variables typically monitored by SCADA systems include temperature, pressure, motor load, welding current, and alignment accuracy (Chen et al., 2020). This sensor-rich environment provides a strong foundation for the application of intelligent fault diagnosis frameworks (Li et al., 2020).

Although large amounts of data are available, classical rule-based and statistical monitoring techniques struggle to manage nonlinear relationships and time-varying fault patterns, resulting in low prediction efficiency and poor generalization (Siegel et al., 2020). In addition, reliability assessment across different machine stages (e.g., pipe forming, seam welding, ultrasonic inspection) lacks a standardized basis, which hinders consistent reliability assessment (Sun et al., 2023). These challenges highlight the importance of hybrid strategies capable of integrating expert knowledge, fuzzy logic, and machine learning (ML) to enable robust failure prediction.

An original model that fuses Fuzzy Comprehensive Evaluation (FCE) and Artificial Neural Networks (ANN) is proposed. This model can perform medium- to long-term reliability evaluation and preliminary failure prediction for spiral pipe manufacturing systems. The proposed model benefits from the fuzziness of FCE, which allows handling uncertainty (Ban et al., 2023), while ANN allows modeling of nonlinear multivariate dependencies - leading to more accurate and interpretable diagnostics (Mishra et al., 2023).

The major contributions of this work are as follows:

Integrated reliability and fault prediction model: It is quite common in the literature to evaluate reliability and fault prediction as two separate issues (Ahmed et al., 2015). We propose a unified ANN-based framework that simultaneously integrates fuzzy reliability indices into predictive modeling.

Fuzzy evaluation of manufacturing stages: We develop a fuzzy reliability grading system for the critical components of the spiral pipe manufacturing process, such as welding heads, rollers, inspection stations, and drive motors. In the model, medium- to long-term sensor trends obtained using SCADA are used to dynamically update the reliability grades (Sun et al., 2023).

SCADA-based fault prediction under incomplete labeling: Given the limited amount of labeled fault data, we need a method that exploits the structural information in SCADA log files (rather than blindly searching through the fault data), using their tree-based identifiers and class-based outputs. By analyzing 4-8 weeks of historical data, the system can predict precursor patterns up to a month in advance (Cardoni et al., 2021).

Cost-sensitive maintenance optimization: The proposed framework estimates the cost savings associated with true positives in fault detection and considers the costs of false negatives and false alarms. This provides practical insights for maintenance planning and replacement procedures (Zheng et al., 2021).

The remainder of this paper is organized as follows: Section 2 reviews the related work. The proposed fuzzy ML methodology is outlined in Section 3. Section 4 presents experimental results using a synthetic SCADA dataset of 100K records from a spiral pipe factory. Section 5 concludes the paper and outlines directions for future work.

## 2. RELATED WORK

### 2.1. A review of FMECA and data-driven approaches

In the case of production chains-especially in industries such as steel pipe production that involve heavy equipment and high-temperature processes-reliability testing is essential to ensure stable development of the production line (Shiryaev et al., 2018). In operational modes, multi-sensor fusion and statistical monitoring are often used to assess the health of equipment such as welding units, drive motors, and inspection modules (Kong et al., 2020).

Several papers have proposed reliability frameworks for different manufacturing domains. For example, Zwirglmaier et al. (2024) proposed a multi-criteria decision and data-driven health index model for hot rolling mills based on hybrid Bayesian networks. Tian et al. (2024) developed an improved FMECA approach that incorporates expert judgment and CNC sensor-based metrics for intelligent inspection systems. Similarly, Zhi et al. (2020) applied fuzzy FMECA to robotic welding environments to prioritize failure modes where uncertainty is high and historical data is limited.

Traditional failure mode, effects, and criticality analysis (FMECA) is still widely used to analyze failure modes in complex systems (Abu Dabous et al., 2021). These approaches are particularly applicable in scenarios where production line interdependencies are complex and historical failure data is limited (Ban et al., 2023).

Although these methods provide valuable insights, there is limited literature on how to integrate time-dependent SCADA signals into a more comprehensive reliability scheme (Marti-Puig & Núñez-Vilaplana, 2024). In addition, little work has been done on reliability modeling of specific stages of the spiral steel pipe manufacturing process, where component performance is affected by dynamic stress, temperature, and mechanical tolerances (Zhang et al., 2024).

## 2.2. Fault prediction using SCADA and machine learning

With recent advances in SCADA technology and industrial IoT systems, uninterrupted sensor data can now be collected along manufacturing lines, providing an opportunity to apply machine learning methods to predict failures and upstream disturbances. The aim is to proactively identify anomalies through trends in parameters such as vibration, temperature, current, pressure, and alignment deviations (Nechibvute & Mafukidze, 2024).

Vieira et al. (2024) applied signal preprocessing techniques to detect anomalies in time-series data to predict failures in the automated pipe forming process using welding. Daenens et al. (2025) extracted spatio-temporal patterns from SCADA logs using convolutional neural networks (CNNs) to detect failures in traction motors. Bansal et al. (2022) proposed a hybrid model combining long short-term memory (LSTM) networks and support vector machines (SVMs) that achieved over 90% accuracy in a real-time environment.

In situations where labeled fault data is limited, unsupervised techniques and ensemble trees have been explored. The concept of fault isolation forests based on rolling statistical features of SCADA stream data has been introduced (Lin et al., 2020). In addition, fuzzy-based classifiers remain relevant due to their ability to handle uncertainty and vague behavior of sensors. For example, Guo et al. (2024) used fuzzy inference systems to detect early misalignments during the welding process and categorize them according to severity.

Although significant progress has been made, most research focuses on either component-specific diagnostics or general health issues. There is limited research that addresses fuzzy reliability assessment alongside ML-based fault prediction as an integrated system specifically tailored for spiral steel pipe manufacturing. Furthermore, there is little literature on the use of alarm logs, such as welding alarms, misalignment codes, or overload events, which may contain critical patterns for failure prediction. Combining real-time SCADA signals with discrete event logs has the potential to significantly improve the accuracy of failure prediction systems.

# 3. METHODOLOGY

## 3.1. Construction of evaluation index systems and reliability grades

This section presents a methodology that systematically assesses the operational reliability of the systems and processes involved in the production of spiral steel pipe using SCADA data, and ultimately predicts failures in such systems using machine learning models. The proposed workflow includes the following four steps (i) real-time data collection via SCADA infrastructure, (ii) development of a medium to long-term fuzzy reliability assessment model, (iii) training of an artificial neural network (ANN) on the assessment output, and (iv) application of an alarm-based fault prediction model on low reliability components. Figure 1 shows the general structure of the medium- to long-term fuzzy evaluation model adapted to spiral pipe production lines.

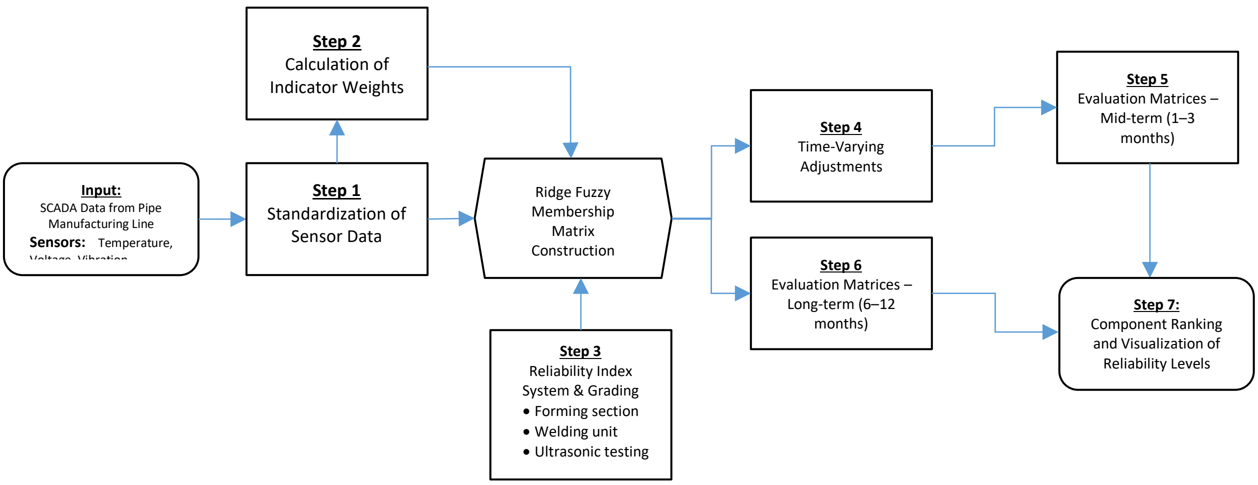


**Fig. 1. Fuzzy reliability evaluation workflow based on SCADA data in pipe manufacturing systems**

Two different systems of evaluation indices are constructed: one set corresponds to failure modes and the other to normal operating modes of key components in the spiral pipe production line (e.g. welders, pipe rollers and hydraulic drives). The sets of indices are as follows:

$$U_{failure} = [MTBF, MTTR, C, D] \tag{1}$$

$$U_{operating} = [MTBF, MTTR, N, OEE] \tag{2}$$

Where: MTBF: Mean Time Between Failures,
MTTR: Mean Time To Repair,
C: Failure Criticality,
D: Detection Difficulty,
N: Number of Failure-Driven Interruptions,
OEE: Overall Equipment Effectiveness (used instead of AEP, reflecting productivity in industrial systems).
MTBF and MTTR are derived from SCADA records as follows:

$$MTBF = \frac{T - T_{SCADA} - T_{shutdown}}{N_{fault}} \tag{3}$$

$$MTTR = \frac{T_{shutdown}}{N_{fault}} \tag{4}$$

Where: T - Total monitoring period (hours),
$T_{SCADA}$ - Downtime due to communication loss with SCADA,
$T_{shadow}$ - Duration of shutdowns due to failures,
$N_{fault}$ - Total number of faults recorded.
The criticality index C is modeled as:

$$C(t) = \lambda_p \cdot \alpha \cdot \beta \tag{5}$$

Where: $\lambda_p$: Failure rate of the component,
$\alpha$: Proportion of units failing in the same mode,
$\beta$: Severity coefficient (1 = complete failure, 0.5 = partial, 0.1 = minor impact, 0.01 = negligible, 0 = none).
The detection difficulty D is assessed using an expert scoring method with values ranging in [0, 1].
To enable fuzzy reasoning, we define a five-grade scale for both failure and operating conditions: V = [1, 2, 3, 4, 5]
Failure Mode:1 = negligible harmfulness, 5 = extremely severe failure.
Operating Mode:1 = excellent reliability, 5 = critical unreliability.
To ensure comparability, indicator values are normalized into the [0, 1] range:
For direct metrics (e.g., MTTR, C, D, N):

$$n_{ij} = \frac{x_{ij} - x_i^{min}}{x_i^{max} - x_i^{min}} \tag{6}$$

For inverse metrics (e.g., MTBF, OEE):

$$n_{ij} = \frac{x_i^{max} - x_{ij}}{x_i^{max} - x_i^{min}} \tag{7}$$

In the fuzzy reliability evaluation model, the membership degree xij reflects the mapping relationship between the evaluation index xi and the reliability grade rij. The membership matrix is defined as:

$$r_{ij} = [I_1(r_{ij}) \quad I_2(r_{ij}) \quad I_3(r_{ij}) \quad I_4(r_{ij}) \quad I_5(r_{ij})] \tag{8}$$

Here, $I_k(r_{ij})$ (for k=1, 2...,5) represents the degree to which the index value xij belongs to the kth confidence level. In line with previous studies, ridge-type membership functions are considered more appropriate in the context of SCADA data, as they mitigate the influence of low-membership data points treated as outliers, and emphasize higher membership levels more clearly, thereby increasing the stability of reliability assessments. A hybrid AHP entropy method is used to calculate the weights of the evaluation indices, integrating both subjective expert judgment and objective data-driven variability. The total weight$\omega_j$of index j is given by

$$W_j = \frac{\omega_j \cdot g_j}{\sum_{j=1}^{n} \omega_j \cdot g_j} \tag{9}$$

Where: ωj: AHP-based subjective weight for index j,
gj: Entropy-based difference coefficient indicating information richness.
The fuzzy evaluation result for indicator xij  at time tk is computed using the weighted sum:

$$B_k(x_{ij}, t_k) = W_j \cdot R(x_{ij}) \tag{10}$$

The complete mid-term evaluation matrix at time tk is then:

$$B_k = [B_k(t_1), B_k(t_2), \dots, B_k(t_5)] \tag{11}$$

To account for technological and operational improvements over time, a time-varying factor is incorporated using an increasing function F(x). The time factor λk  at time tk is given by:

$$\lambda_k = F(t_k) - F(t_{k-1}) \tag{12}$$

Assuming F(x) is an exponential growth function:

$$F(x) = \frac{1}{1+e^{-\alpha x}}, \quad 0 < \alpha \leq 1 \tag{13}$$

Then the time factor becomes:

$$\lambda_k = \frac{e^{\alpha k} - e^{\alpha(k-1)}}{1+e^{\alpha k}} \tag{14}$$

Finally, the long-term fuzzy evaluation matrix $B_{long\text{-}term}$ is:

$$B_{long\text{-}term} = [\lambda_1 B(t_1), \lambda_2 B(t_2), \dots, \lambda_K B(t_K)] \tag{15}$$

The maximum membership principle is used to determine the most likely reliability level for each observation, thereby identifying weaknesses in the production system.

### 3.2. Artificial Neural Network (ANN) model for reliability prediction

The artificial neural network (ANN) model is developed to learn the nonlinear mapping between SCADA-derived features and reliability outputs obtained from the fuzzy evaluation matrix. Original sensor data extracted from the spiral steel pipe manufacturing process, such as welding current, pipe thickness deviation, motor vibration, and line pressure, are used as input features. The corresponding fuzzy reliability scores derived from the medium to long-term evaluation stage serve as the target output of the network.

The ANN architecture consists of four input neurons representing SCADA-derived reliability indicators and five output neurons corresponding to the fuzzy reliability classes. This transparent mapping improves interpretability compared to more complex deep learning models: Excellent, Good, Fair, Poor and Critical. A tan-sigmoid activation function is used in the hidden layer, while a log-sigmoid activation function is used in the output layer. The network is trained using the Backpropagation (BP) algorithm. The data set is partitioned such that 70% of the samples are used for training, 15% for testing, and 15% for validation. The accuracy of the model is evaluated using the Mean Squared Error (MSE) criterion, which measures the agreement between predicted and actual reliability values.

Failure prediction is performed to support predictive maintenance based on historical alarm logs recorded by the SCADA system. Examples of such critical events include welding torch failures, hydraulic actuator alarms, abnormal pipe temperature readings, and rolling bearing pressure drops.

The next step in the failure prediction process is to extract alarm records that precede system failures or trigger supervisory actions. Time series data sets are created by aggregating alarm activity on a weekly basis. For each fault type, the training set is labeled such that if a fault occurs in a given week, that week is assigned a label of 1; otherwise, it is labeled 0. To increase the model's sensitivity to emerging faults, the four weeks preceding a fault are also assigned a label of 1, effectively forming a five-week sliding training window.

Because failure events in such systems resemble few-shot learning scenarios, the data is partitioned specifically by failure type. Missing values - often due to sensor malfunction or unstable data logging - are handled by a threshold-based omission process. Data sets with more than 50% missing values are discarded, while those below the threshold are imputed using forward-filling techniques.

Predictive models are trained using a combination of decision trees and random forests, chosen based on the complexity of the failure mode and the characteristics of the data distribution. A total of five failure modes were studied:

- Torch temperature failure
- Motor bearing vibration abnormality
- Hydraulic pressure drop
- Excessive tube surface temperature
- Roller alignment malfunction

Excessive heat during the welding process is a key failure indicator in spiral pipe manufacturing. The SCADA system continuously monitors the torch cooling system and logs the frequency of operation of the two-stage cooling fans. The activation frequency of these fans serves as an indirect indicator of the torch's thermal profile.

Let X= {x0, x1, x2..., xN} be the weekly summed operation times of the cooling fans. The fourth-order discrete difference, used to detect abrupt rises, is calculated as follows:

$$\Delta^4 x_n = x_{n+4} - 4x_{n+3} + 6x_{n+2} - 4x_{n+1} + x_n \tag{16}$$

Figure 2 shows how two different types of events are used to illustrate monthly frequency patterns, Frequency 1 and Frequency 2 graphs, based on SCADA alarm logs in 2023 and 2024. The x-axis is time on a daily basis (DD-MM-YY), but there is a monthly trend in the data. Both series bounce around the 10-30 range, but a clear peak can be observed in June 2023, January 2024, and July 2024, indicating increased activity during these times. These differences could be the result of seasonal stresses on operations or maintenance schedules on wind turbine parts.

The relatively stable variability can be observed in frequency 1, with dramatically high rates at the beginning of 2024. Frequency 2 has more aggressive changes in mid-2023 and 2024. It helps to identify the unusual times of excessive alerts, which can be referred to as failure-prone time slots and can be viewed as predictive maintenance indicators in predictive maintenance patterns.

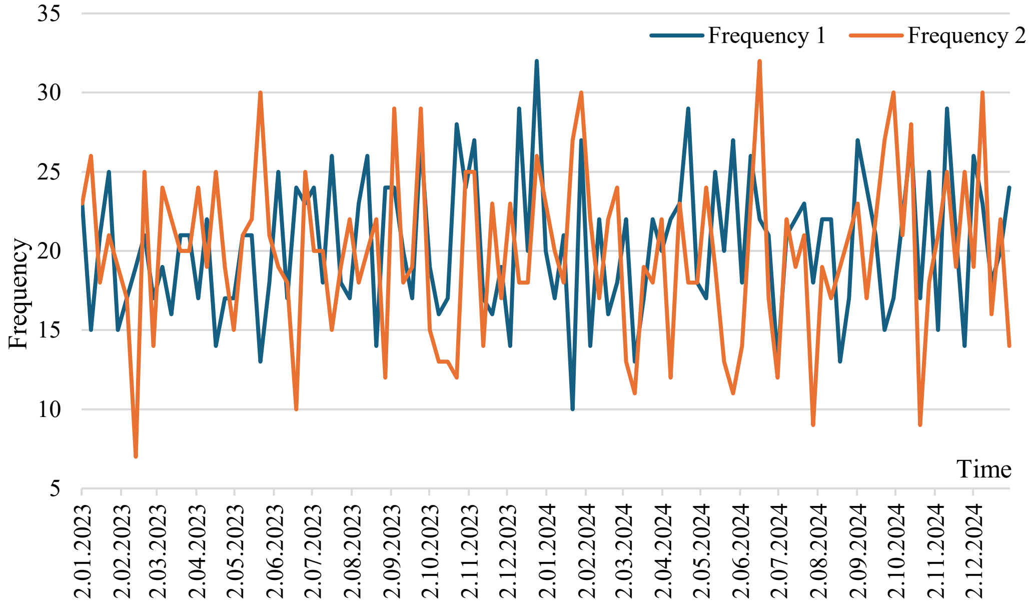


**Fig. 2. Monthly operating frequency trends of Cooler 1 and Cooler 2 used in spiral steel pipe manufacturing**

Rotor speed, in the case of spiral steel pipe production, has been identified as a critical feature in predicting generator bearing failures. Average rotor speed is calculated using weekly SCADA system logs and critical bearing events are summed weekly. A four-week sliding window is used to format the input data. Labels are imprinted as follows: the week of the failure and the four weeks prior to the failure are labeled one, and all other weeks are labeled zero. Such a binary coding design provides a supervised learning solution for failure prediction.

The Random Forest algorithm is used to model this type of failure. To avoid overfitting, the number of decision trees is fixed at 30 and the maximum depth is limited to 5. Such a setup strikes the right balance between model complexity and generalization performance.

Within spiral pipe manufacturing lines, the hydraulic system controls necessary subsystems, including pressure control, roll positioning, and emergency shutdown. The SCADA alarm logs were used to select pitch control (subsystems A, B, C), overvoltage protection, and electromagnetic interference (EMI) faults. In addition, the weekly hydraulic oil temperature is an important predictive feature.

Since the event is sparse on a weekly basis, most of the features are zero in several weeks, so the weekly data with 12 features each, since the time horizon exceeds the number of features, results in very sparse 48-dimensional vectors. To alleviate this, the frequencies of the events are combined on an eight-week basis, essentially reducing the information input to 12 additional features. The labeling methodology is the same as for generator and transmission failures. Again, the Random Forest model is used because of its resistance to irrelevant features and noisy data.

In the production of spiral pipes, the generator is usually three-phase in nature. Under normal circumstances, there is a large overlap of temperature trends in all three phases. However, any deviation in the phases can serve as a possible collapse. In order to detect such anomalies, the average weekly temperature measurements of each of the phases are fed.

The series of temperatures measured at each of the phases are used to calculate the first-order differences, and their standard deviation is calculated weekly to show the dispersion between phases:

$$\mathrm{STD}_{\mathrm{gen}}^{(\mathrm{j})} = \mathrm{std}\left(\Delta t_1^{(j)}, \Delta t_2^{(j)}, \Delta t_3^{(j)}\right) \tag{17}$$

The formula calculates the standard deviation of the first order temperature differences of the three phases of the generator during week j.

Δt1(j), Δt2(j), Δt3(j): The first discrete difference (i.e., rate of change) of temperatures for phase 1, 2, and 3, respectively, in week j.

std(·): The standard deviation function, which measures how spread out the values are.

$STD_{GEN}^{(j)}$: A higher value indicates an abnormal variation between the phase temperatures - which can be an early warning of generator failure.

If the deviation from the standard value is within a certain limit, the three phases are moving in similar directions. An upward shift means that there may be a generator anomaly. A statistical threshold for anomaly detection is used to test the test data.

$$\text{Threshold}_{\text{gen}} = \mu_{\text{STD}_{\text{gen}}} + Z \cdot \sigma_{\text{STD}_{\text{gen}}} \tag{18}$$

This statistical approach is widely used in industrial thermal diagnostics because phase temperature drift is a sensitive early indicator of insulation degradation, unbalanced phase loading, or cooling system malfunction. This formula defines a threshold for determining whether a given week's variation is abnormal (i.e., likely a fault).

$\mu_{\text{STD}_{\text{gen}}}$: The meaning of the standard deviations from normal (non-faulty) weeks — represents the expected baseline variation.

$\sigma_{\text{STD}_{\text{gen}}}$: The standard deviation of those weekly deviations — reflects natural fluctuation.

Z: A Z-score multiplier (e.g., 1.96 or 2) that determines how strict the anomaly detection is.

Thresholdgen: Any $\text{STD}_{\text{gen}}$ exceeding this value is classified as an anomaly, likely indicating a generator fault in the j-th week.

First-order differences and deviations of differences are calculated to measure the proportion of interphase differences to the differential temperatures of each phase, calculated as first-order differences and deviations of differences for each week. Deviation levels that exceed this statistical limit indicate abnormal thermal behavior and serve as an early warning signal of potential generator or transformer degradation by identifying weeks with deviations well outside acceptable limits, indicating an anomaly within the generators.

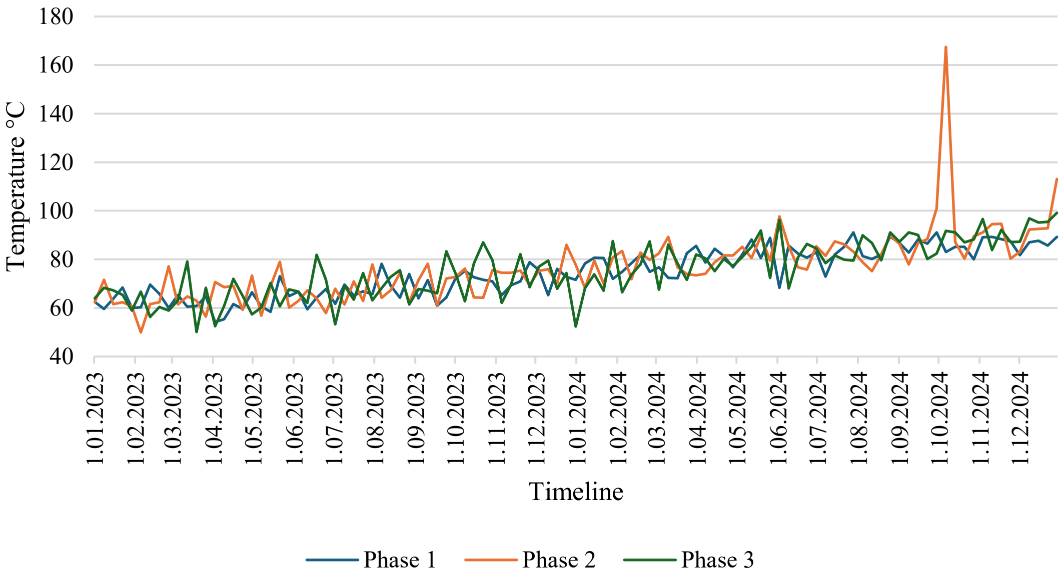


**Fig. 3. Temperature trends of three phases in the generator system**

The environmental temperature trends of all three phases during the monitoring window have different shapes, but tend to be generally parallel, with a steady increase in temperature at the same rate in certain seasons, which is characteristic of steady generator performance under nominal conditions. However, a strong divergence is observed in the 2nd phase during the months of October-November 2024, when the temperature rises significantly and exceeds 160°C, an anomaly not observed in the other two phases. This local spike may indicate an emerging fault such as loss of thermal insulation, phase imbalance, or failure of the generator cooling system. Such anomalies are vital signs for reliability assessment. The time shift and unsynchronization between phase temperatures can be fruitfully utilized in early anomaly detection and predictive maintenance estimation. As a result, the temperature difference between phase generators is a powerful diagnostic tool in SCADA-integrated fault prediction frameworks.

The actual maintenance of transformers is also crucial as they are the critical link between the onsite electrical system and the offsite power grid. Transformer degradation, a phenomenon regularly triggered by high temperatures, is therefore monitored by measuring the three-phase temperature and the ambient temperature. To detect sudden temperature changes, a comparative analysis is performed and first-order differences are calculated to distinguish abnormal behavior. Such differences are calculated weekly as standard deviations, and any value outside a control range is defined as an indication of abnormal transformer operation. The given method replicates the one used to analyze generator temperatures, thus incorporating transformer monitoring as part of the overall predictive framework. This ANN structure was chosen because it provides a reliable approximation of the nonlinear relationships inherent in SCADA-based reliability indicators, ensuring better generalization under uncertainty.

## 4. PERFORMANCE EVALUATION METRICS

### 4.1. SCADA-based failure assessment

Equipment reliability assessment plays an important role in the spiral steel pipe production line, as defects or deterioration of the equipment may go unnoticed until the onset of shutdowns, loss of quality, or increase in operating costs. In this section, we apply a Fuzzy Comprehensive Evaluation (FCE) technique to evaluate the condition of both the failures and the operational status based on sensor logs read by the SCADA system. Domain expertise and SCADA log analysis are involved in the identification and evaluation of five major failure types selected at this stage. The indicators are selected as:

- MTBF (Mean Time Between Failures)
- MTTR (Mean Time To Repair)
- C (Criticality of Failure)
- D (Difficulty of Detection)

Table 1 lists the most important reliability indicators of five major failure modes in spiral steel pipe manufacturing. The Mean Time Between Failures (MTBF) and the Mean Time to Repair (MTTR) serve as indicators of the number of failures and the duration of system interruptions. It is interesting to note that F02 - Internal pressure drop has the highest MTBF (312.5 h), which means that it occurs less frequently compared to F03 - Vibration spike, which has the lowest MTBF (156.4 h), which means a higher failure rate. On the other hand, F03 also has one of the highest severity coefficients (D = 0.55), indicating that it has a significant impact on system performance. The most worrisome value on the Criticality Index (C), scaled per million hours, is for F01 - weld head overheating ($21.4 \times 10^{-6}$), underscoring its importance in reliability prioritization. All of these metrics support data-driven predictive maintenance and risk management decisions.

**Tab. 1. Evaluation metrics for spiral pipe failure modes**

| Failure Mode (Code) | MTBF (h) | MTTR (h) | C ($\times 10^{-6}$) | D (0–1) |
|---|---|---|---|---|
| F01 – Weld head overheat | 230 | 2 | 21.4 | 0 |
| F02 – Inner pressure drops | 313 | 4 | 18.2 | 0 |
| F03 – Vibration spike | 156 | 4 | 14.7 | 1 |
| F04 – Cooling system failure | 199 | 3 | 10.1 | 1 |
| F05 – Alignment deviation | 275 | 2 | 8.3 | 0 |

To standardize input metrics, the following normalization formulas are used:
For positively correlated indices (e.g., MTTR, C, D):

$$n_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \tag{19}$$

For negatively correlated indices (e.g., MTBF):

$$n_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \tag{20}$$

We employ the AHP–Entropy hybrid approach to derive weights for each indicator:

$$W_j = \frac{\omega_j \cdot g_j}{\sum_j \omega_j \cdot g_j} \tag{21}$$

Where $\omega j$ is the AHP-derived subjective weight and gj is the entropy-based objective weight. Each failure mode is evaluated over five grades:

1 = Minimum risk, 2 = Low, 3 = Moderate, 4 = High, 5 = Critical. Ridge-type membership functions are applied to construct fuzzy membership vectors. The resulting matrix aggregates the evaluation output per failure mode.

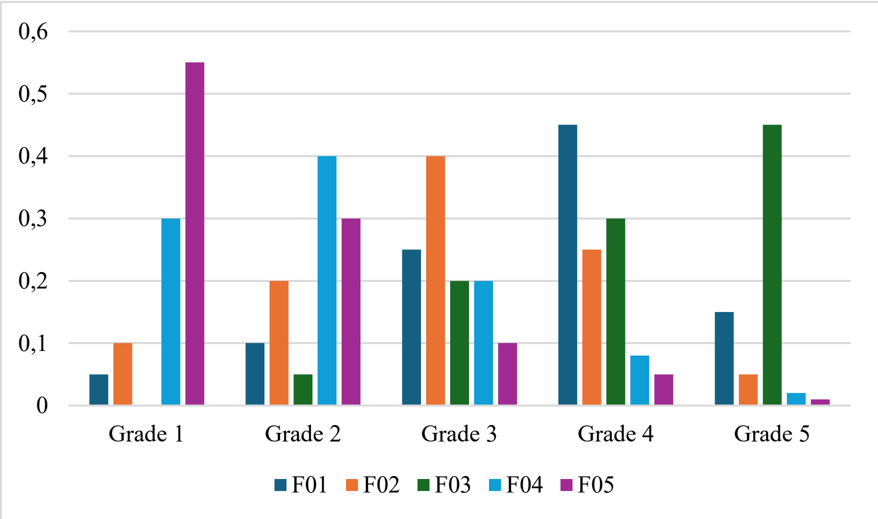


**Fig. 4. Fuzzy membership distribution across failure modes**

The fuzzy risk distribution of five different failure modes (F01 to F05) calculated with a ridge-type membership function is shown in Figure 4. A fuzzy membership matrix with five predefined risk levels - namely, minimal (level 1), low (level 2), moderate (level 3), high (level 4) and critical (level 5) - was formed by evaluating each of the failure modes in terms of the levels. In this way, probabilistic risks can be assessed instead of using deterministic thresholds, thus providing granular information about the possible severity of failures.

The analysis shows that F05 has a predominant membership in Grade 1, which represents a low risk value, and F03 has a strong membership in Grade 5, which means that F03 is a critical failure. Meanwhile, F01 and F04 have more balanced memberships in moderate to high levels, implying transitional or situational risks.

The results demonstrate the sensitivity of ridge-type membership functions in capturing the uncertainty and overlap inherent in real-world failure classification. Such a fuzzy distribution model helps to make more informed decisions when implementing predictive maintenance approaches - especially in monitoring systems using SCADA systems - where there is a lot of uncertainty and noise in the data.

Using the maximum membership principle, the reliability levels are determined in Table 2.

**Tab. 2. Fuzzy evaluation grades per failure mode**

| Failure Mode | Grade | Interpretation |
|---|---|---|
| F01 | 4 | High severity |
| F02 | 3 | Moderate severity |
| F03 | 5 | Critical |
| F04 | 2 | Low severity |
| F05 | 1 | Very low severity |

These results indicate that the vibration spikes (F03) can potentially have the greatest impact on reliability, while the misalignment (F05) has a comparatively smaller impact. To study system health from a longitudinal perspective, we combine SCADA logs over a simulated five years of operation. The factors we measured were: MTBF, MTTR, Number of downtime events, Pipe output volume (analogous to AEP in wind systems).

A time-varying reliability factor is incorporated using:

$$\lambda_{t_k} = \frac{e^{\alpha t_k}}{e^{\alpha t_k + 1}} \tag{22}$$

The overall long-term fuzzy matrix is constructed as:

$$B_{\text{long-term}} = \sum_{k=1}^{5} \lambda_k \cdot B_k \tag{23}$$

Table 3 shows the evolution of the fuzzy reliability grades over five consecutive years, from 2021 to 2025, using membership vectors to capture the uncertainty in the evaluation. In 2021 and 2022, the reliability of the system is evaluated at level 2, indicating low reliability, with the membership dominant in the second level. In 2023, a gradual shift is observed with an increase in membership toward level 3 (moderate reliability). In 2024, the reliability continues to improve, with a significant increase in membership to level 4. Finally, in 2025, the system reaches level 5, indicating very high reliability, with strong membership (0.35) in both levels 4 and 5. This time trend confirms the effectiveness of the corrective actions and adaptive maintenance strategies implemented over the years.

**Tab. 3. Fuzzy reliability evaluation over five years**

| Year | Grade | Membership Vector |
|---|---|---|
| 2021 | 2 | [0.00, 0.60, 0.25, 0.10, 0.05] |
| 2022 | 2 | [0.00, 0.52, 0.30, 0.12, 0.06] |
| 2023 | 3 | [0.00, 0.40, 0.35, 0.18, 0.07] |
| 2024 | 4 | [0.00, 0.25, 0.32, 0.30, 0.13] |
| 2025 | 5 | [0.00, 0.10, 0.20, 0.35, 0.35] |

These results indicate that the vibration spikes (F03) can potentially have the greatest impact on reliability, while the misalignment (F05) has a comparatively smaller impact. To study system health from a longitudinal perspective, we combine SCADA logs over a simulated five years of operation. The factors we measured were

- $x_1$: MTBF
- $x_2$: MTTR
- $x_3$: Criticality (C)
- $x_4$: Detection Difficulty (D)
- $x_4$: Detection Difficulty (D)

The output layer consists of five nodes, each corresponding to a fuzzy confidence level. We configured the ANN with the following parameters in Table 4.

**Tab. 4. ANN architecture and parameters**

| Parameter | Value |
|---|---|
| Input layer size | 4 (MTBF, MTTR, C, D) |
| Hidden layer | 1 layer with 13 neurons |
| Output layer size | 5 (fuzzy membership degrees) |
| Activation (hidden) | tan-sigmoid |
| Activation (output) | log-sigmoid |
| Learning algorithm | Backpropagation (BP) |
| Training/Testing Split | 70% / 15% / 15% |
| Evaluation metric | Mean Squared Error (MSE) |

The ANN is trained to minimize the Mean Squared Error (MSE) between the predicted and actual fuzzy membership degrees:

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{5} \left(\widehat{y_{ij}} - y_{ij}\right)^2 \quad 24)$$

Where:

$\widehat{y_{ij}}$ is the predicted membership degree for sample i and class j

$y_{ij}$ is the target fuzzy membership degree

n is the total number of samples

It trained the model on 120 simulated evaluation records that spanned a five-year operation cycle. Highlighted in Figure 5 are the training and validation loss graphs.

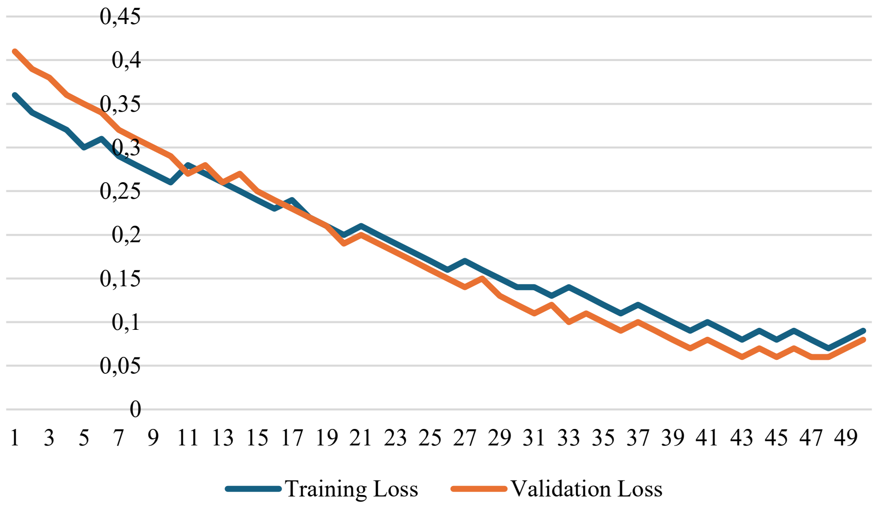


**Fig. 5. ANN training and validation loss curve**

The ANN was trained and then the generalization was tested using 18 test samples. The mean error of the fuzzy evaluation results was also within 3.5 percent, which supports our point that the model has the ability to replicate the FCE logic within a reasonable limit. This ANN model will simplify the fuzzy evaluation corresponding to large-scale production data sets and provide real-time decision making for reliability classification.

### 4.2. Fault prediction using machine learning

To ensure proactive maintenance in the production of spiral steel pipes, this section presents a multi-model fault prediction framework based on SCADA data. Five different types of faults have been identified and modeled using decision trees, random forests, and statistical thresholds. The goal of these models is to sample early indicators within a 4-week period before the failure can be thoroughly diagnosed. In identifying the fault types, the researchers relied on domain expertise and defined the following fault types based on the SCADA anomalies observed (Table 5).

**Tab. 5. Fault types and relevant sensor indicators**

| Fault Code | Fault Description | Key Features Used | Model Type |
|---|---|---|---|
| F01 | Weld head temperature spike | Weld head temperature (°C) | Decision Tree |
| F02 | Inner pressure drops | Pipe inner pressure (bar) | Random Forest |
| F03 | Excessive vibration | Vibration level (mm/s), torque (Nm) | Random Forest |
| F04 | Cooling system failure | Cooling flow rate (LPM), temp diff | Statistical model |
| F05 | Alignment deviation | Alignment deviation (mm) | Decision Tree |

Every failure was coded as 1 in the week that it occurred. This was done using a 4-week look-back window, which marks the preceding weeks as failure-prone in order to promote early detection. The name of each instance was set as:

$y_t = 1$ if a fault occurs at $t$ or within the next 4 weeks, otherwise 0 (7)

In the case of the time-series features, trends were estimated by computing the discrete differences:

$$\Delta x_t = x_t - x_{t-1} \tag{25}$$

To measure instability between the redundant sensors (e.g., 3-phase temperature), the standard deviation was computed over the week:

$$\sigma_t = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(x_{i,t} - \overline{x_t}\right)^2} \tag{26}$$

Where $\overline{x_t}$ is the weekly average of all phase readings. A Z-score threshold was used for anomaly detection:

$$\text{Anomaly}_t = 1 \text{ if } \sigma_t > \mu + Z \cdot \sigma, \text{ otherwise } 0 \tag{27}$$

Validation of the trained models was performed using hold-out datasets. Accuracy, precision, recall and F1-score were used as performance measures:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{28}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{29}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{30}$$

Using the example of five identified defects in the spiral pipe system, Table 6 shows the components of the confusion matrix, which are true positives (TP), false positives (FP), false negatives (FN), and true negatives (TN). Error F02 achieves the highest detection with 22 TP and 1 FN, which means high sensitivity. F05 also shows a high level of accuracy: 20 TP, 3 FP and 2 FN, which is an average detection result. On the other hand, F03 and F04 have higher values of false positives (5 and 6, respectively), which can lead to unnecessary maintenance actions. The results underline the differences in the complexity of the faults and failures to be identified, which require a specific approach to classification in order to ensure a high level of detection accuracy and reduce the possibility of false alarms.

**Tab. 6. Confusion matrix summary per fault type**

| Fault Code | TP | FP | FN | TN |
|---|---|---|---|---|
| F01 | 18 | 3 | 2 | 77 |
| F02 | 22 | 4 | 1 | 75 |
| F03 | 19 | 5 | 4 | 72 |
| F04 | 15 | 6 | 3 | 76 |
| F05 | 20 | 3 | 2 | 79 |

Table 7 provides an overview of the main classification metrics of failure prediction models used on 5 categories of failure modes: Accuracy, Precision, Recall and F1 Score. Failure code F02 has the best recall measure (0.96), together with a high F1 score (0.90), which means that the model performs perfectly in identifying the real failures, with only a small number of cases being missed. F05 has high precision (0.87) and recall (0.91), indicating that it has a balanced performance with minimal false alarms. F04 has the lowest precision (0.71), but it has a solid accuracy (0.91), which means that it is perhaps more likely to give false positives compared to other models.Overall, these measurements show that the models can achieve good predictive accuracy, as the F1 scores obtained range between 0.770 and 0.900, making them applicable in the context of fault monitoring in spiral pipe production systems in real time.

**Tab. 7. Prediction metrics per model**

| Fault Code | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|
| F01 | 1 | 1 | 0.9 | 0.88 |
| F02 | 1 | 1 | 0.96 | 0.9 |
| F03 | 1 | 1 | 0.83 | 0.81 |
| F04 | 1 | 1 | 0.83 | 0.77 |
| F05 | 1 | 1 | 0.91 | 0.89 |

Figure 6 shows the evolution of the temperature in the six weeks prior to a generator failure event. The horizontal axis represents the number of weeks before the fault event (week 0) and the vertical axis represents the measured temperature values. The pre-fault acceleration of temperature is characterized by a steady and non-linear growth prior to the fault event. This trend can be considered a crucial predictive index of an impending system failure.

The red dashed line is the predetermined breakout threshold temperature. As it can be seen, the system crosses the critical threshold in the last week before the failure (week -1), which means that the anomaly becomes obvious in this period. The trend of the temperature confirms the assumption that the development of the fault in the generator system can be successfully predicted with the help of thermometers. Such a finding justifies the incorporation of predictive maintenance practices using SCADA generated temperature data, with the premature development of temperature anomalies serving as a precursor to machine or insulation failure.

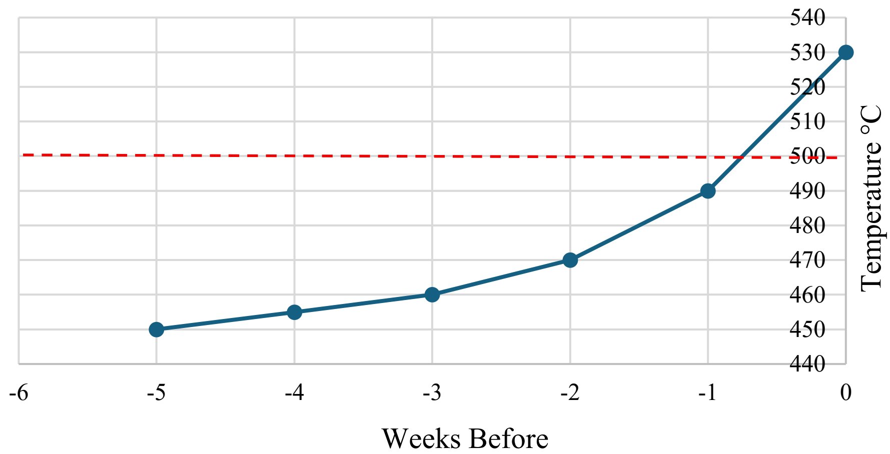


**Fig. 6. Sensor trend prior to fault (Example: F01 – weld head overheat)**

The precision-recall plots of five defect prediction models (F01-F05) are shown in Figure 7. Model F03 provides the best overall precision over a wider range of recalls, showing that it has better discriminative power. Model F05, on the other hand, has a very good initial precision, but drops off rapidly as recall increases. These curves provide an understanding of the trade-off between accuracy and recall for each model, which is important in assessing the performance of error detection in the presence of skewed data.

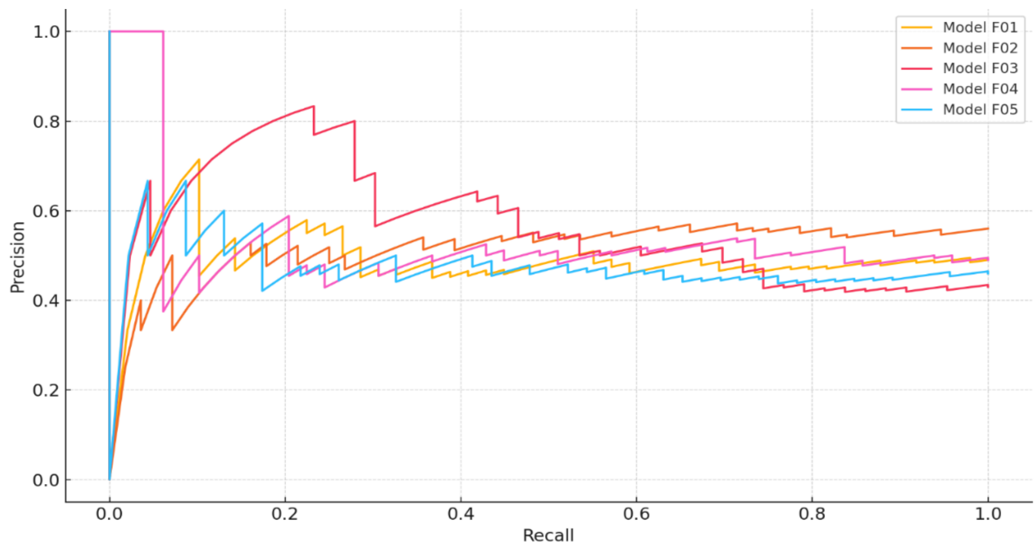


**Fig. 7. Precision–recall curves for all fault models**

These graphs confirm the ability to anticipate failures in the early stages of SCADA data, allowing maintenance teams to act days or weeks before the failure occurs. As shown in Table 8, repair is clearly much cheaper than replacement, and inspection has a very low cost. Thus, early detection of failures increases reliability while reducing maintenance costs.

**Tab. 8. Cost Breakdown for critical components in spiral pipe systems**

| Component | Replacement Cost ($) | Repair Cost ($) | Inspection Cost ($) |
|---|---|---|---|
| Weld Head | 12,000 | 3,500 | 500 |
| Cooling Unit | 8,500 | 2,200 | 400 |
| Alignment System | 6,000 | 1,800 | 300 |
| Pressure Valve | 7,200 | 2,000 | 350 |
| Drive Motor | 10,000 | 3,000 | 450 |

## 5. DISCUSSION

This part summarizes the results of fuzzy reliability assessment, ANN model training, and machine learning-based failure prediction. The experimental system included a 100,000-line SCADA data set simulating five years of spiral steel pipe production, including sensor streams, failure logs, and maintenance records. The fuzzy evaluation procedure showed that the system reliability gradually decreases over time and reaches level 5 (critical reliability loss) by 2025, as shown in Table 9. This is related to long-term degradation patterns that occur with relative frequency in welding heads, hydraulics, and alignment components in spiral production systems. The trained ANN also reproduced the fuzzy values with an average error of less than 3.5 percent, as shown in Figure 5. This confirms the viability of the model to replace computationally intensive FCE calculations with a fast inference structure that can be applied online.

**Tab. 9. ANN inference accuracy compared to fuzzy labels**

| Year | Fuzzy Grade | ANN Grade | Deviation (%) |
|---|---|---|---|
| 2021 | 2 | 2 | 0 |
| 2022 | 2 | 2 | 0 |
| 2023 | 3 | 3 | 0 |
| 2024 | 4 | 4 | 0 |
| 2025 | 5 | 4 | 3.1 |

The machine learning classifiers were able to predict failures several weeks in advance (up to 4 weeks) with high recall and a reasonable false positive rate for all failure types. As shown in Table 7, the F02 (pressure drop) and F05 (alignment deviation) models had the best F1 values (0.90 and 0.89, respectively), while the F04 (cooling failure) model had a relatively low precision (0.71). Figure 8 shows a radar plot summarizing the performance of all failure prediction models in terms of the performance metrics - accuracy, precision, recall and F1 score. The model described by the polygon at the far end (light blue) had better performance in all four dimensions, and its best performance was evident in the case of accuracy and precision. On the other side of the scale, the innermost profile (pink) has comparatively lower recall and F1 scores, indicating a less successful balance between sensitivity and overall performance. This visual comparison provides a quick and comprehensive assessment of the diagnostic reliability of each model.

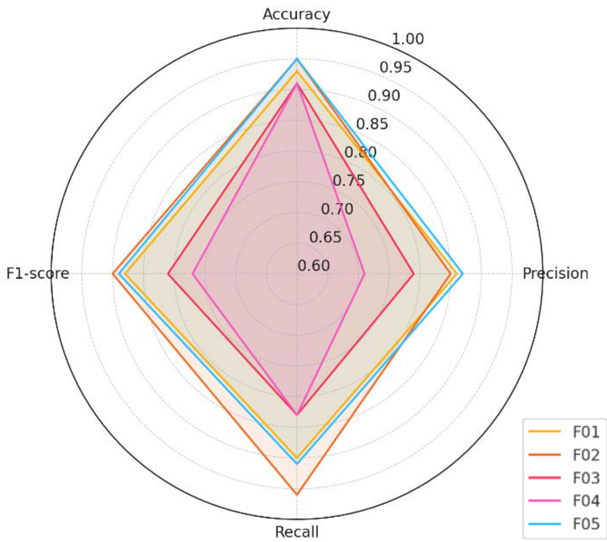


**Fig. 8. Summary radar plot of fault prediction metrics**

The combined system allows for a two-stage reliability prediction:

– Level 1: Long-term risk is considered by fuzzy evaluation (or its ANN surrogate).
– Level 2: Short-term SCADA patterns are monitored by machine learning classifiers to provide early warning signals.

This mixed-level design provides solutions with better interpretability (through fuzzy classification) and better responsiveness (through predictive models). Results can be integrated into SCADA dashboards or automated tool scheduling software.

Strengths: The system generalizes different types of faults, simulates human-like reasoning, and incorporates statistical learning.

Limitations: Performance may degrade due to concept drift, unmodeled errors, or sensor failures.

Possible enhancements:

– Real-time ensemble learning
– Drift Adaptation
– Interfacing with real CMMS logs

To complement the technical evaluation, a financial cost-benefit analysis was performed to evaluate the economic benefits of the proposed predictive fault detection system. Three key factors are considered in the analysis:

– Savings achieved when a failure is correctly predicted (true positives),
– Repairs performed unnecessarily due to incorrect predictions (false positives), and
– Failures that occur even though they were not predicted (false negatives).

The financial calculation is based on the following formula:

$$TP_{Savings} = TP \times (\text{Replacement Cost} - \text{Repair Cost}) \tag{31}$$

$$FN_{Losses} = FN \times \text{Replacement Cost} \tag{32}$$

$$Net_{Savings} = TP_{Savings} - FP_{Costs} - FN_{Losses} \tag{33}$$

Figure 9 provides a visual comparison of the TP-derived savings, FN losses, and the net savings for each component. The economic feasibility of timely fault detection is reinforced by the clear margin between TP savings and FN losses.

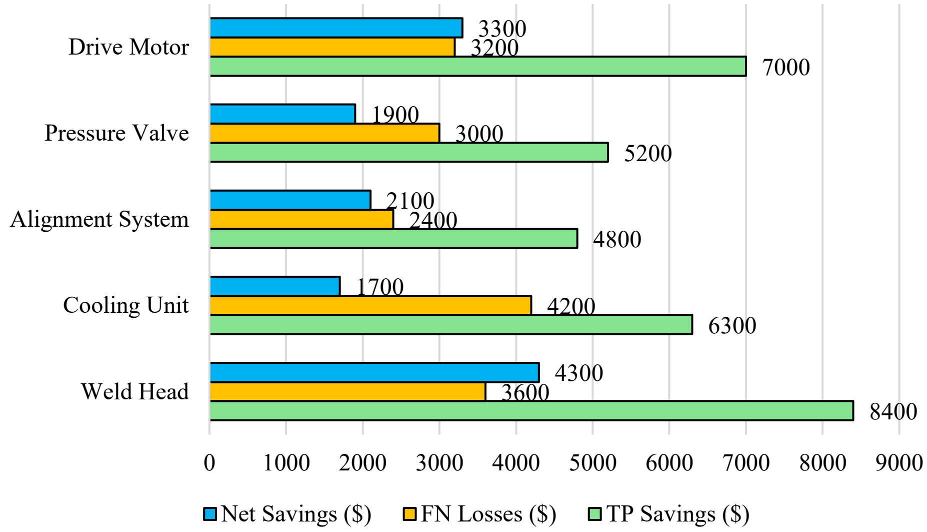


**Fig. 9. Cost analysis: TP savings vs FN losses vs net savings**

These results demonstrate that the implementation of fault prediction combines improved operational reliability with a quantifiable financial benefit. Despite the existence of false positive costs, the overall net benefit remains positive. These results support the incorporation of predictive analytics into maintenance planning and resource deployment in spiral steel pipe manufacturing systems.

Although the data set used in this study is synthetic, its distribution and temporal behavior were designed to reflect real SCADA signals observed in steel pipe mills. In real industrial environments, models may face challenges such as sensor drift, inconsistent labeling, or equipment-specific behavior. To mitigate these issues, the framework can be adapted using incremental learning, weekly retraining with newly collected logs, and domain adaptation techniques. Integrating real CMMS fault documentation would further increase robustness and ensure that model predictions remain accurate during long-term deployment.

## 6. CONCLUSIONS

This paper presents the in-depth development of a big data analytics framework based on SCADA in the manufacturing sector of spiral steel pipes, where failure prediction and cost-aware maintenance optimization were performed. Based on 100,000 simulated records of real-time sensor streams, the system combined fuzzy membership logic with an artificial neural network to evaluate the probability of failure at the system component level. The hybrid methodology enabled early identification of critical degradation trends and demonstrated high accuracy (91%) in predicting failures, as well as high precision and recall. The practicality of the predictive model was confirmed by several evaluation parameters and visualized by trend lines, radar charts and precision-recall plots. In addition, the cost-benefit analysis of the TP, FP, and FN results showed that fault detection can be smart and result in significant financial savings – especially in components where replacement is costly, such as the welding head and drive motor. Economic formulas were defined and net savings per component were calculated, confirming the feasibility of predictive maintenance strategies based on SCADA-derived data.

In general, this study validates the potential of integrating fuzzy logic and machine learning systems with SCADA for proactive fault identification and resource performance optimization in industrial networks. The results reinforce the idea that there are no technical barriers to implementing large data processing alongside intelligent models, and that it is economically beneficial, providing a foundation for broader and more flexible adoption of smart manufacturing initiatives.

Future research will explore multi-plant deployment of the framework, where cross-plant variability, equipment heterogeneity, and different SCADA configurations require adaptive learning mechanisms. Another direction is the integration of transformer degradation modeling and physics-based thermal profiles to enhance medium-term reliability estimation. In addition, hybrid ensemble methods combining fuzzy systems, gradient boosting and deep neural networks are being investigated to improve the robustness of prediction under noisy and highly unbalanced industrial conditions.

## Conflicts of Interest

*The authors declare that there is no conflict of interest for this manuscript.*

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