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Original Article

Diagnosis of the Failures of a Complex Industrial System by Neuro-Fuzzy Networks Optimized by a Genetic Algorithm (ANFIS-GA): A Case of the Franceville Brewery

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Abstract *- Fault diagnosis in intricate industrial operations is a difficult task, especially in the African context, due to the stochastic interaction between symptoms and faults, a lot of inputs and outputs, and the difficulty of acquiring characteristic data (spectral study, sound, vibration, electrical quantities, etc.) of the operating state through specialized sensors. Furthermore, if this diagnosis is performed online, a fast time algorithm is required to account for the system's instantaneous changes. With the objective of reducing maintenance costs, improving productivity, and increasing machine availability, we develop an online fault diagnosis model for a dynamic process based on an adaptive neuro-fuzzy inference system (ANFIS) based on the production history and associated faults. This algorithm is optimized by the algorithm based on gene (GA) to learn the defect-production correlation of a brewery from historical production and process failure data. This method, based on the data, such as the format of bottles produced, daily production hours, number of manufactured bottles without defects per day, number of manufactured bottles with defects per day, and downtime of production subsystems, allows us to extract the data-driven defect-symptom correlation. Optimizing an ANFIS classifier for fault diagnosis reduces the computation time and increases accuracy, thus allowing the integration of newly identified faults in the process. In conclusion, the proposed model, based on GA-ANFIS, is tested on the process of the Franceville brewery in Gabon. The results on our dataset are better than other types of data from some studies according to their accuracy (88.97%), precision (89.23%), sensitivity (73.20%), and specificity (96.27%).*

Keywords *- ANFIS, Complex industrial system, Diagnosis of the failures, Reliability, Optimization.*

1. Introduction

The lack of qualified personnel in industries using the latest technological development tools, such as the brewery industry in Africa, generally causes prolonged stoppages of certain processes, resulting in huge financial losses that lead to job losses and, thus, increase poverty [1]. However, failure detection and identifying damaged components in real time can prevent process stoppages by improving process operation and reducing process downtime [2]. Various strategies for identifying and detecting flaws have been proposed and studied in the literature. These approaches may be separated into three parts: quantitative model-based methods [3-5], qualitative model-based methods [6-8], and data-based methods [9-10]. We developed a data-based diagnostic system using data analysis with decision-making methods such as neural networks and fuzzy logic due to the difficulty and imprecision in the mathematical modeling of complex systems such as brewing industries, as well as the erratic behavior of such a system. Therefore, the concept of combining fuzzy logic and neural networks has been developed to overcome these problems [13]. Using a neural network and a fuzzy logic theory combines the advantages of neural networks to extract complex relationships between defects and symptoms from historical process data with those of fuzzy logic to improve the system's ability to handle uncertainty.

Artificial intelligence approaches such as neural networks have been widely studied in the field of engineering [11, 12] as well as in process fault identification [13-18]. However, the use of Neural networks in the classification of failures in complex systems is limited due to their black-box behavior and the impossibility of taking into account the systems' operation rules and modeling the knowledge about these processes. Therefore, the notion of integrating fuzzy logic with neural networks is applied to overcome these problems [19]. The use of a fuzzy neural network combines the advantages of neural networks to extract complex relationships between defects and symptoms from historical process data with those of fuzzy logic to improve the system's ability to handle uncertainty. The system of adaptive neuro-fuzzy inference (Anfis) is a neural network connexionism with a fuzzy inference system that has the ability to bring together the advantages of both in a unified model since it incorporates machine learning and fuzzy inference ideas. The inferential system is represented as a set of fuzzy IF-THEN rules that can learn the approximation of nonlinear functions. Therefore, ANFIS is considered a universal approximator [20].

Several authors have worked on data-driven industrial system diagnosis using the ANFIS method. The most recent work is discussed in this section. S. Rajabi et al. [21] suggested a technique for defect diagnostics in rotating industrial machinery depending on mutation entropy, signal processing, and a neuro-fuzzy classifier with numerous outputs (ANFIS). The approach is automated, and its performance is not sensitive to unbalanced data. As stated by the authors, this method permits the automatic selection of fault frequency bands and combines higher accuracy with more efficient implementation than other methods. In the same vein, N. Md. Nor et al. [22] have worked on diagnosing industrial chemical processing systems by applying the ANFIS method to enhance fault classification performance. The authors combine some data processing methods such as PCA or multiscale kernel Fisher discriminant analysis (KFDA). The findings showed that the suggested KFDA-ANFIS multiscale framework improved classification accuracy by an average of 87.02% when compared to the PCA-ANFIS (78.90%) and FDA-ANFIS (70.80%) multiscale frameworks. C. Abdelkrim et al. [23] created an adaptive neuro-fuzzy inference system in 2020 to identify and categorize bearing defects in industrial gear motors. [46]

A test campaign was conducted on an industrial facility (a wheel conveyor) to collect data. The results obtained show that the proposed approach can reliably detect and classify various faults with, for all training and test data, an accuracy of 97.38%. We can also mention the study done in 2020 by the authors of [24], who developed a neuro-fuzzy classifier to identify the fault of stator windings in an industrial machine. The AI-based neuro-fuzzy classifier was shown to be capable of generating rules and class labels on its own using a given set of experimental data, whereas the fuzzy classifier required user involvement to specify the rules and fuzzy membership.

In the field of brewing industries, Thimotée Kombé et al. [25] developed a dynamic supervision graphical interface for failure prognosis using the IA-PLC combinatorial approach applied to the plant of the Sociétés Anonymes des Brasseries du Cameroun (SABC). They achieve good results with an RMSE of 0.2142. However, the performance of the generalization of this network on the test data could have given good results if the dataset had been more consistent because the authors observed an accuracy of 79.6%.

The work of [21] allows us to validate ANFIS as an excellent method for real-time (online) diagnosis of complex industrial systems because, according to the authors, its performance is not sensitive to unbalanced data. The authors of [22] allow us to consider a hybridization of the ANFIS method to improve its performance because, in his last study, one of the authors of this article [25] shows that the number of data points and the type of data points affect the results in terms of reduction of the prediction error and accuracy. For this purpose, we are going to hybridize ANFIS with a metaheuristic to improve the results in terms of both learning time and accuracy. Indeed, it has been shown in the literature that metaheuristics are excellent optimizers of machine learning algorithms [26–30].

Many data management difficulties exist in current facility maintenance procedures and processes, such as data loss, time lost searching for information, lack of interoperability, and so on. A lack of adequate decision-making processes and maintenance planning might raise operating costs, impacting facility production quality. Proper data management methodologies and technologies should be applied to address these issues and shortcomings successfully. This research aims to demonstrate that the production history (type of bottle, number of hours of daily production, and number of defective bottles produced per day) can characterize particular failures in a complex system like a brewery. It is a matter of selecting an algorithm that allows the model's learning capacity to be associated with the generalization of knowledge on the operation of the complex system.

To achieve this objective, we will structure our work as follows: In part 2, we present the materials and methods used. This section will explain the data collection, experimental procedures, and statistical analysis (metrics) used to validate the results. In Section 3, we present the results obtained, and in the fourth section, we start a discussion on the scope of this study and the significance of the results. We end with a conclusion.

2. Materials and Methods

2.1. Data Collection

This research began three years ago in a brewery industry located in Franceville, Gabon. We monitored the beer manufacturing process. Throughout these three years and on a daily basis, we observed and listed the failures that occurred on this chain, taking care to identify the failing system, the cause of the failure, the duration of the failure, the failure modes, and the effects. Over these three years, we have collected an important database, which will be used in this study. Statistically, we have obtained Figure 1, which presents the time and frequency of equipment failure in this process. We are especially concerned. with the following subsystems: the unpacker, the washer, the filler, the labeler, the case packer, and the coder. This figure identifies the duration, number, and frequency of failures.

We can observe that for the 166th day, the case packer had a downtime of 300 minutes and the labeler a downtime of 220mn. The data from this study is explained in Table 1 below. The experimentation through these data will follow the procedure presented by the block diagram in Figure 2 below. This figure shows how the research will be conducted.

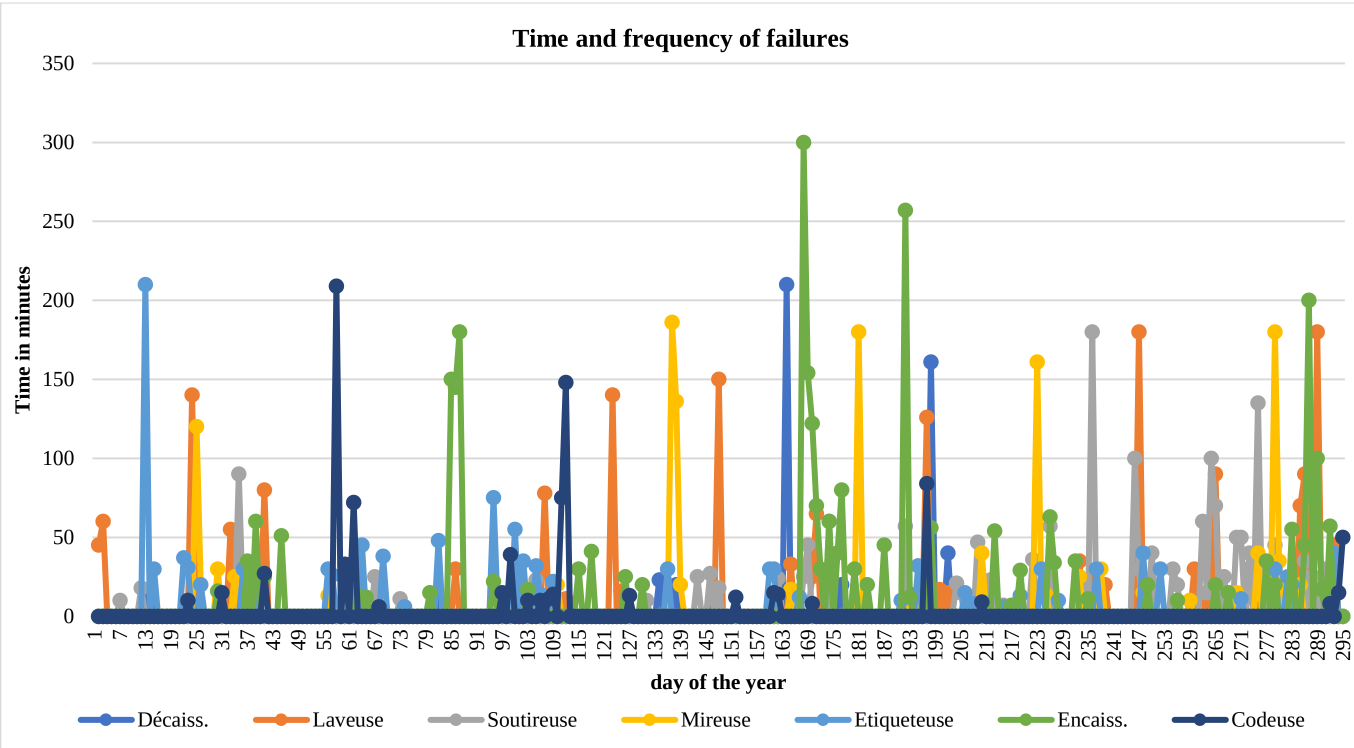

Fig. 1 Defaults in one year

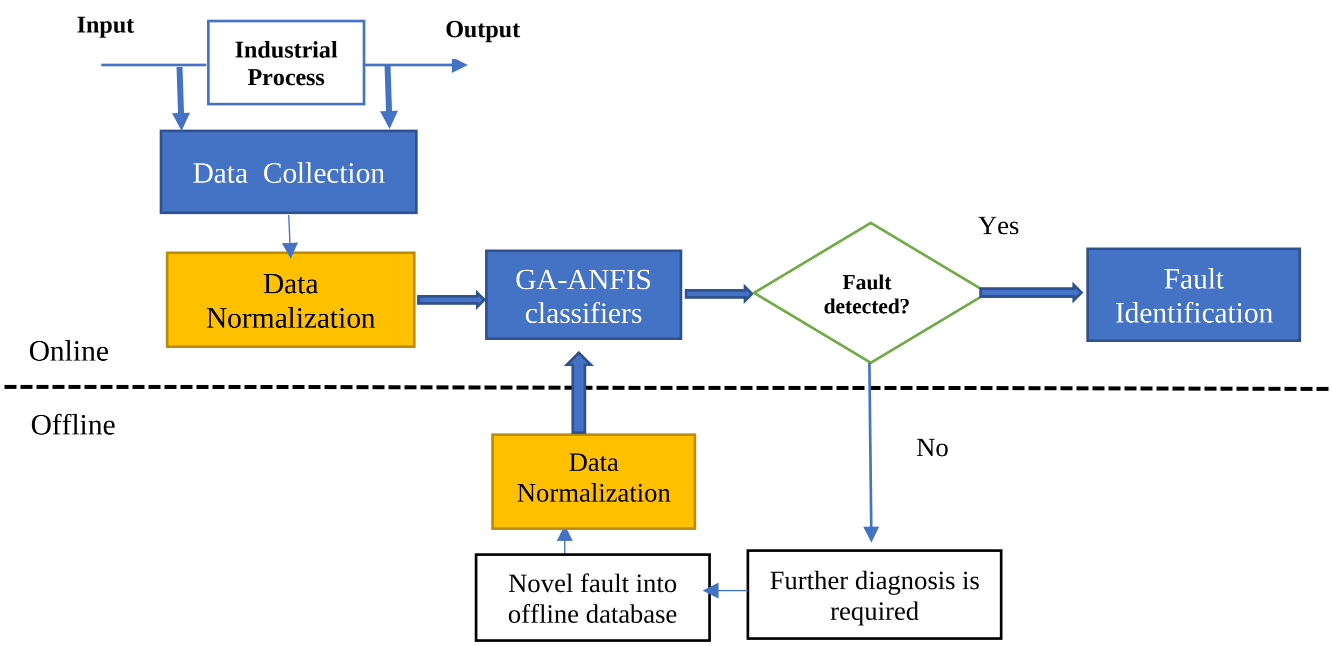

Fig. 2 Synoptic of the experimental research procedure adopted

Table 1. Characterization of input data

Input Dataset	Characteristics	Sizes	Hypothesis
Format	Bottle sizes	65cl, 60cl,33 cl	The size of the bottle produced has an impact on the failures
Paid hours	Daily running time of the process	Duration in Minutes	The daily operating time has an impact on the occurrence of a failure
Filler counter	Number of bottles produced daily	Integer	The number of defective bottles per day characterizes a type of failure
Store entries	Number of bottles produced without faults	Integer	
Downtime	Downtime of the unpacker, washer, filler, sizer, labeler, packer and coder	Duration in Minutes	The downtime of the subsystems characterizes the failure or not of the industrial process

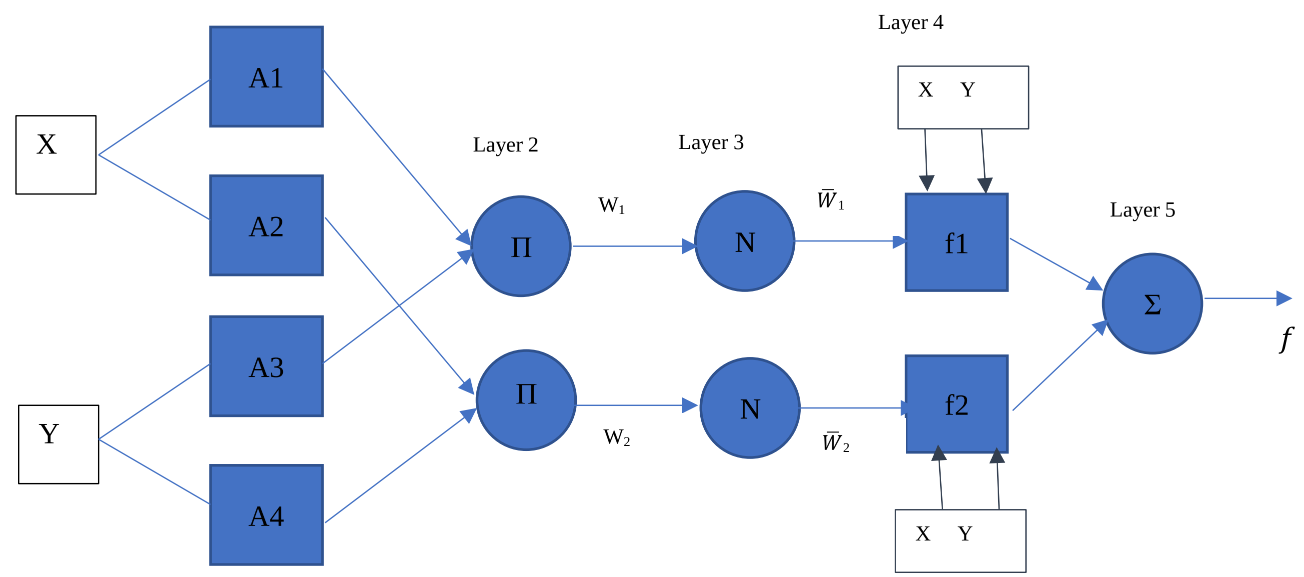

Fig. 3 Five layers of ANFIS architecture

As we can see in Figure 2, the experimentation is done in two phases: one offline and the other online. The online procedure detects new failures that are not listed and inserts them into the offline database to enrich it. These data are classified using an artificial intelligence algorithm that combines machine learning and fuzzy inference bases to provide the capability of automatically generating rules from data. This is the adaptative fuzzy inference neural system enhanced by a genetic algorithm (GA-ANFIS) presented below.

2.2. Theoretical study of the method

2.2.1. Adaptive Neuro-Fuzzy Inference System (ANFIS)

Lofti Zadeh [31] claims that, in human perception, nearly all classes offer fuzzy boundaries. The marriage of the learning ability of the neural network and the fuzzy logic's knowledge representation ability gave rise to the fuzzy neural network. The disadvantage of the inability of ANN to explain the decision and the weakness of learning in fuzzy logic has been overcome.

The ANFIS seem to be a very important neuro-fuzzy system. ANFIS, developed by Jang in the year 1993 [20], is based on Sugeno's fuzzy model, in which a rule is represented by the following equation 1:

$$R_k\text{: } IF \mu_A(x) AND \mu_B(y) THEN f = p_k x + q_k y + r_k \quad (1)$$

Where k is the number of rules, and Ai and Bi are fuzzy membership functions denoted by the rule's antecedent. Rk, Pk, qk and rk are the linear parameters of the consequent part of the kth rule. All of the layered architecture of ANFIS includes a fixe or an adaptive node, as shown in Figure 3 below.

The following paragraph shows the mathematical modeling after each layer:

- Layer 1. Each node in this layer is an adaptive node with a node membership function that can be Gaussian, triangular, or trapezoidal. The outputs of this layer are calculated using the following membership functions (Equations 1 and 2).

$$o_i^1 = \mu_A(x), i = 1,2\ldots \quad (1)$$

$$o_i^1 = \mu_B(x), i = 1,2\ldots \quad (2)$$

- Layer 2 computes the firing force of a rule via the product operation Π shown in Equation 3.

$$O_i^2 = w_i = \mu_{A_i}(x) \times \mu_{B_i}(y) \quad , \quad i = 1,2\ldots. \quad (3)$$

- Layer 3 calculates the normalized firing force of a rule from a previous layer, as shown in Equation 4

$$O_{i\ i}^3 = \bar{w}_i = \frac{w}{\sum w_j} \qquad i = 1,2\ldots. \quad (4)$$

- In layer 4, each node represents the consequent part of the fuzzy rule. The linear coefficients of the consequent rule are trainable. The output is given by equation 5.

$$O_{i\ i}^3 = \bar{w} \bullet f_i = \bar{w}_i \bullet (p_k x + q_k y + r_k), \quad i = 1,2\ldots. \quad (5)$$

p_k , q_k and r_k are linear parameters.

- Layer 5 nodes perform defuzzification of the consequent part of the rules by summing the outputs of all rules with equation 6
-

$$O_i^5 = \sum_{i=1}^{n} \bar{w}_i \bullet f_i = \sum_{i=1}^{n} \bar{w} \bullet (p_k x + q_k y + r_k) \quad (6)$$

The success of ANFIS can be attributed to the robustness of the results it provides. ANFIS has a generalization capability as large as multilayer perceptron and other machine learning techniques. ANFIS can also take clear inputs, represent them as membership functions and fuzzy rules, and generate clear outputs from fuzzy rules for reasoning purposes. This opens the door to applications that involve fuzzy inputs and outputs. ANFIS also has drawbacks, such as a high computing cost owing to its complicated structure and gradient learning. This is critical for applications with a lot of input features. The membership function characteristics and the appropriate parameters are the customizable parameters in ANFIS. This necessitates a more efficient training process capable of adjusting the settings. The computing cost is proportional to the complexity of the parameters.

As a result, the greater the number of parameters in the ANFIS design, the greater the training and computing expenses. In an ANFIS, the fuzzy inference system has an obvious effect on the modeling accuracy. Therefore, ANFIS has two main visions:

- Slow convergence
- The possibility of becoming trapped in the local minima.

The inference system can be optimized by metaheuristic and heuristic techniques such as GA to overcome these limitations. In order to efficiently solve our online fault classification problem for our industrial system, which is made of several inputs, we opt to optimize ANFIS to search for faults in near real-time by decreasing the processing time and minimizing the errors.

2.2.2. Genetic Algorithm Adaptive Neuro-Fuzzy Inference System (GA-ANFIS)

The evolutionary genetic algorithm is a hunt optimization technique inspired by biological and natural selection principles. It is routinely utilized to solve tough issues that would otherwise take a lifetime to complete. It is based on terminology such as " population", which is a subcategory of all possible (coded) solutions to the problem. "Chromosomes" are a part of this solution to this problem. The gene is the position of an element of a chromosome.

Another terminology used is "crossover", which is the selection of a parent and the production of one or more offspring using the parent's genetic information. Mutation terminology is used to maintain and introduce diversity into the genetic population. Another word used in GA representation is a phenotype, which refers to the subgroup in the solution area in which answers are represented in the same manner they are in the real-world scenario.

The stopping conditions of GA are: when there has been no improvement in the population during X iterations when we reach an absolute number of generations, and when the value of the objective function has reached some predefined value. In the literature, there are many applications of GA on routings, such as the TSP (traveling salesman problem) [33-35], shop floor scheduling [36-38], automatic programming [39-41], machine learning, and ANFIS optimization problems [42-45].

Table 2 presents the algorithmic structure of the GA. That has shown the contribution of data-driven analysis in the maintenance of industrial systems that have shown the contribution of data-driven analysis in the maintenance of industrial systems. Figure 4 represents a schematic adaptation of ANFIS-GA from [52], where a detailed description of the model flowchart is given.

2.3. Performance Evaluation Metrics

The measures of RMSE and MSE ("root mean square error"), MAE (mean absolute error), SE(standard error), and accuracy of the models evaluate the performance of the models, as follows from the formulas below:

MAE: it measures only the magnitude of errors and does not concern with their direction. The lower the MAE, the higher the accuracy of a model. Mathematically, the MAE can be expressed in equation 6.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \quad (6)$$

Table 2. Algorithmic structure of the GA

(a)	Initialization: Randomly create a chromosome population and calculate the efficiency of each chromosome using the fitness function.
(b)	Operators GA: ((I) Selection: selecting the two best chromosomes in the population based on fitness; using the selected chromosomes as parents to produce an offspring of new child chromosomes and the next generation. (ii) Crossover: the parent chromosomes intersect randomly with a certain probability and produce the new child. If there is no intersection, the child's chromosomes will be identical to the parents. (iii) Mutation: This operation is used for a random modification to change some of the genes inside the chromosomes. It is possible to adjust the population diversification and improve the searchability through mutation to prevent the algorithm's convergence to the local optimum.
(c)	Evaluation: As the objective function of the optimization problem, the fitness function usually has a specific form at this stage.

Table 3. Confusion matrix and metric

Confusion Matrix		Target			
		Positive	Negative		
Model	Positive	a	b	Positive predictive value	a/(a+b)
	Negative	c	d	Negative predictive value	d/(c+d)
		Sensitivity	Specificity	Accuracy= (a+d)/(a+b+c+d)	
		a/(a+c)	d/(b+d)		

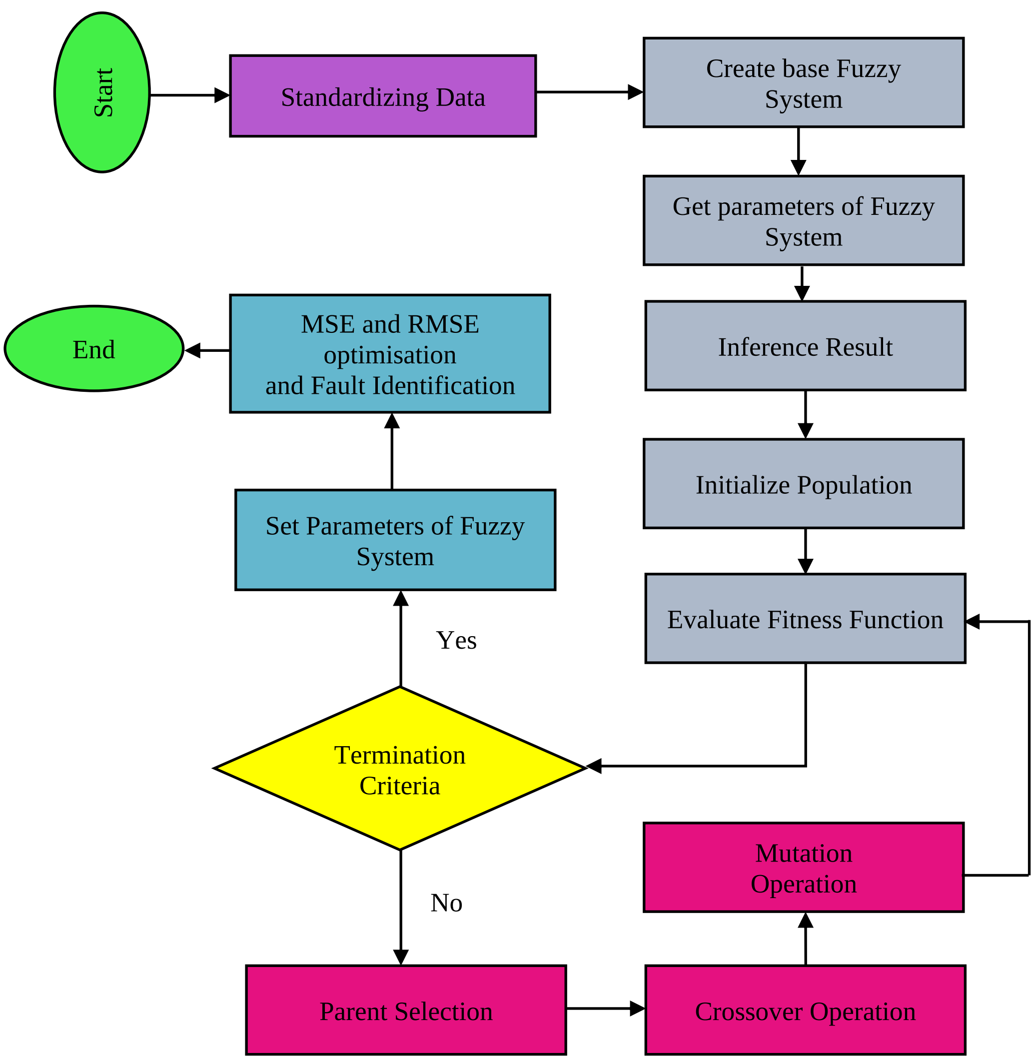

Fig. 4 GA- ANFIS architecture

Mean Square Error (MSE): MSE increases exponentially with increasing error. A good model will have an MSE value close to zero.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (7)$$

RMSE: the lower the RMSE, the better the model and its predictions. A higher RMSE indicates a large gap between the residual and the ground truth. The RMSE can be used with different features because it can be used to determine whether or not the feature improves the prediction of the model.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (8)$$

CF (confusion matrix): it is a matrix which allows us to compute the model performance.

Here are some definitions you need to remember for a confusion matrix, as shown in table 3:

- Accuracy: the proportion of the total number of predictions that were correct.
- Precision: the fraction of accurately detected positive instances.
- Negative predictive value: the proportion of negative cases that were correctly identified.
- Sensitivity (Recall): the proportion of genuine positive instances appropriately detected.
- Specificity: the fraction of real negative situations detected accurately.

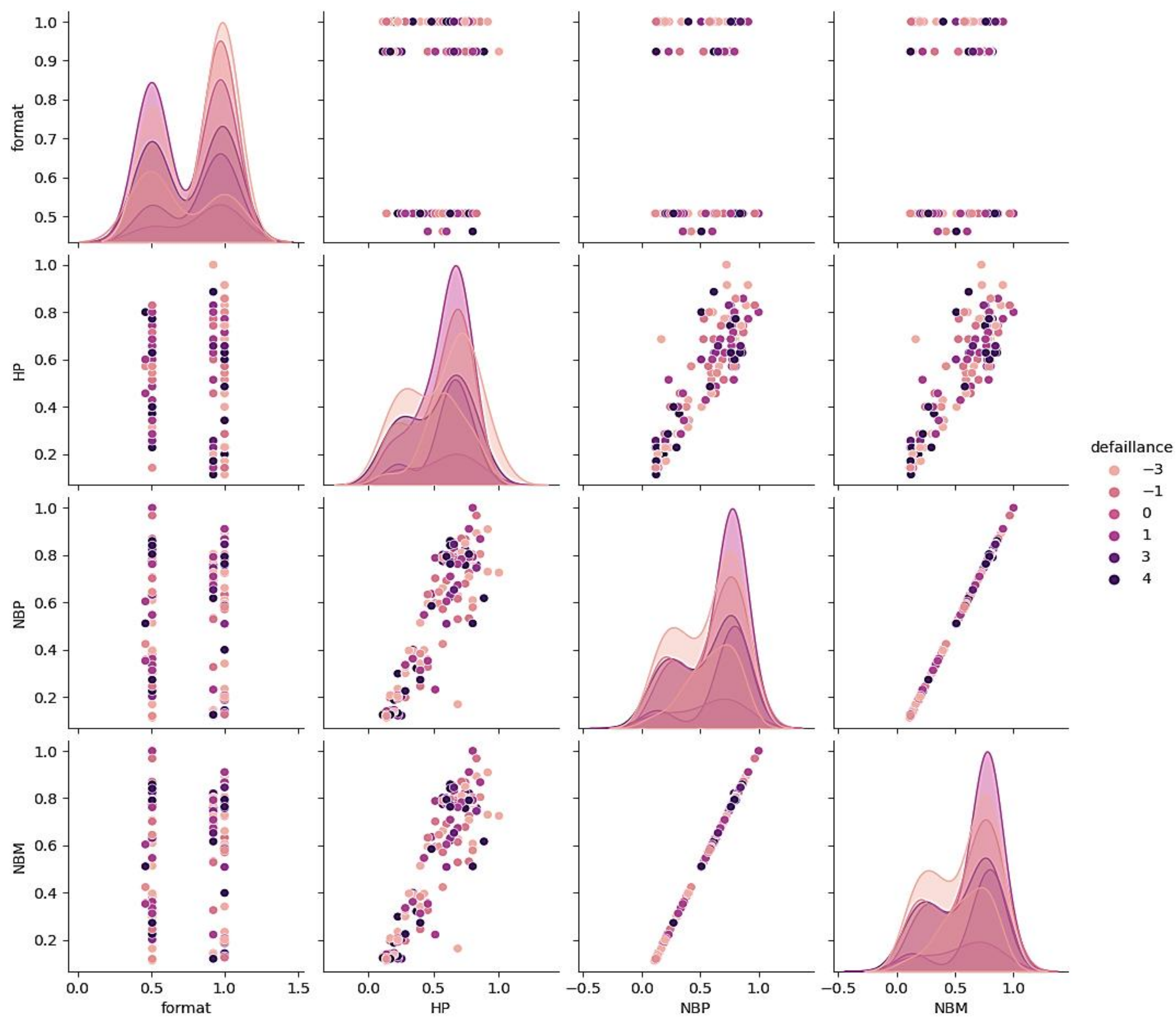

Fig. 5 Features Pair plot

3. Results

3.1. Pre-processed data

Figure 5 shows the bivariate scatterplots for all combinations of the variables. Each variable is plotted against the rest of the variables. The diagonal plots are the density distributions of the variables. Table 1 shows a list of the encoded variables. The failures are presented in different colors with the legend in Figure 5 and coded according to Table 4:

By visualizing these data, we notice that the different classes of failure are difficult to separate linearly, so it will be impossible to use a linear model or a non-optimized machine learning algorithm to get good results. Hence the choice of optimized ANFIS.

3.2. Analysis of the Genetic Adaptive Neuro-Fuzzy Inference System

Figures 6 and 7 show the 160-day failure prediction curves for the year 2021, respectively. As we can see, the predicted curve in blue seems to follow the historical failure data in green closely. The prediction seems better with the GA-optimized ANFIS because the errors are smaller, as presented in Table 4.

Table 4. Defect coding

Code	-3	-1	0	1	3	4
Failures	Washer	Filler	Waxing machine	Labeler	Case packer	Coder

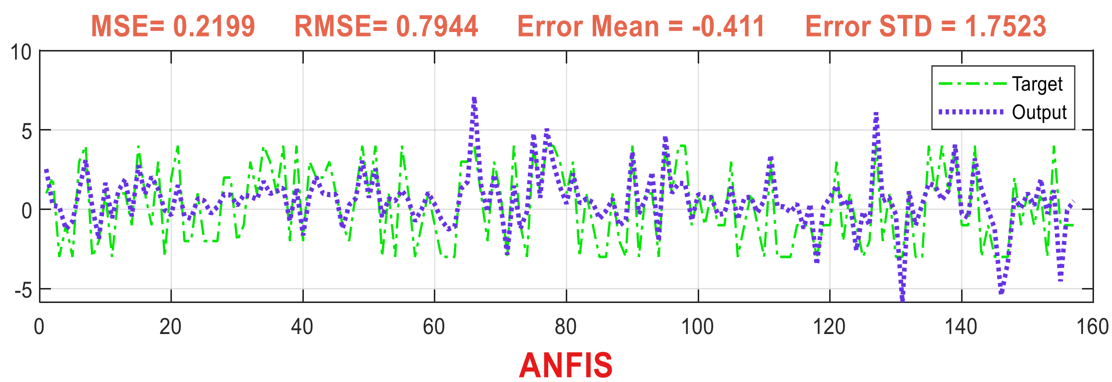

Fig. 6 GA- ANFIS architecture

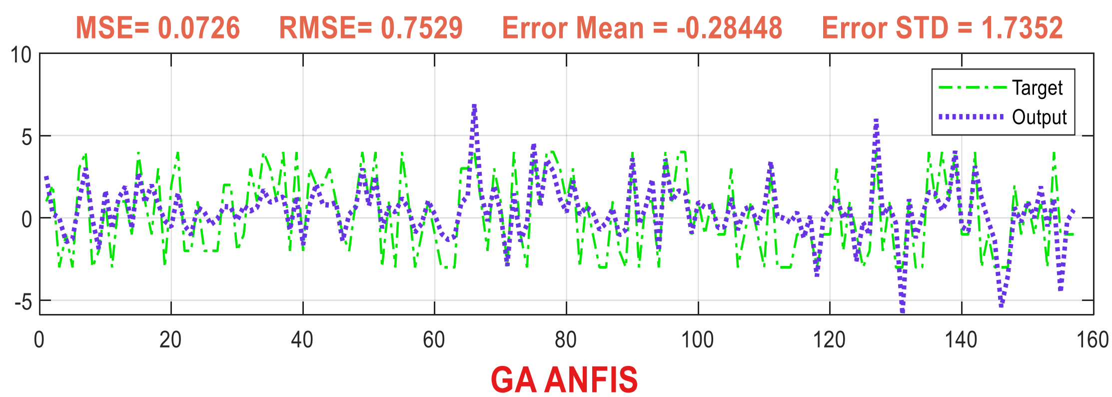

Fig. 7 GA- ANFIS architecture

Table 5. Confusion matrix and metric

	MSE	RMSE	Error Mean	%Error standard
ANFIS	0.2193	0.7944	-0.4110	1.7553
GA-ANFIS	0.0726	0.7529	0.6281	1.7352

It can be noticed that the optimization of ANFIS provides the best results. In comparison, the MSE of GA-ANFIS is more than 10 times lower than that of simple ANFIS.

Figures 8 and 9 show the confusion matrices generated on Matlab to determine the classification metrics.

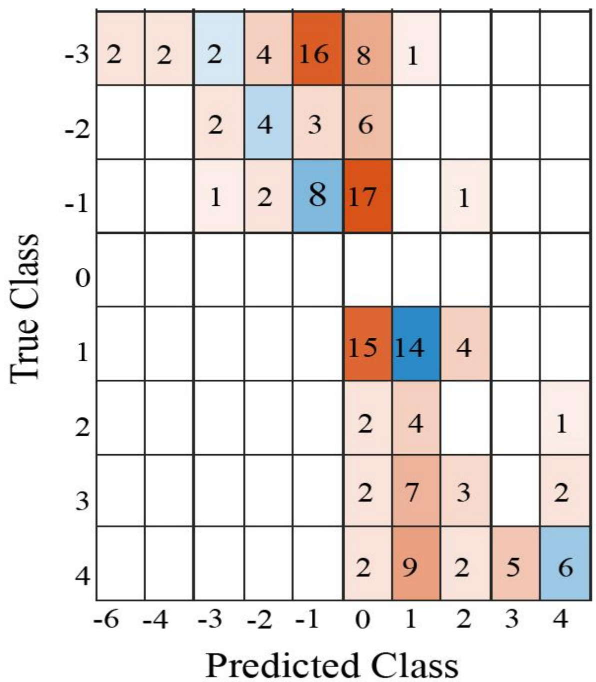

Fig. 8 GA- ANFIS Confusion matrix

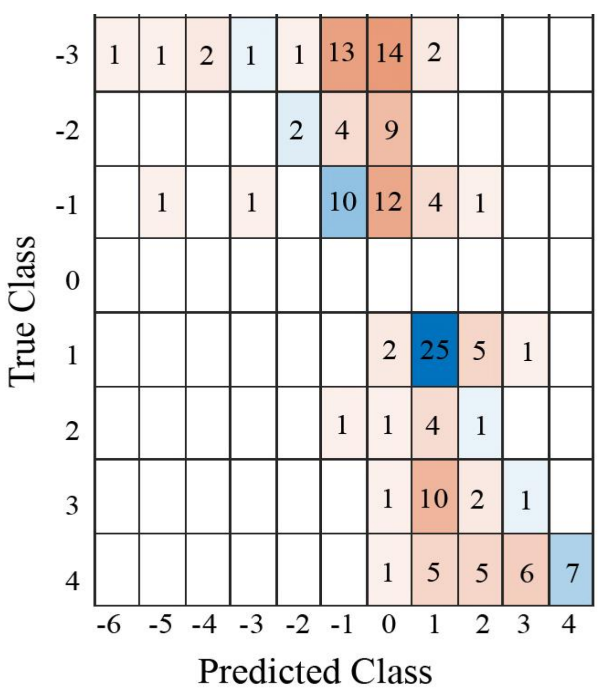

Fig. 9 ANFIS Confusion matrix

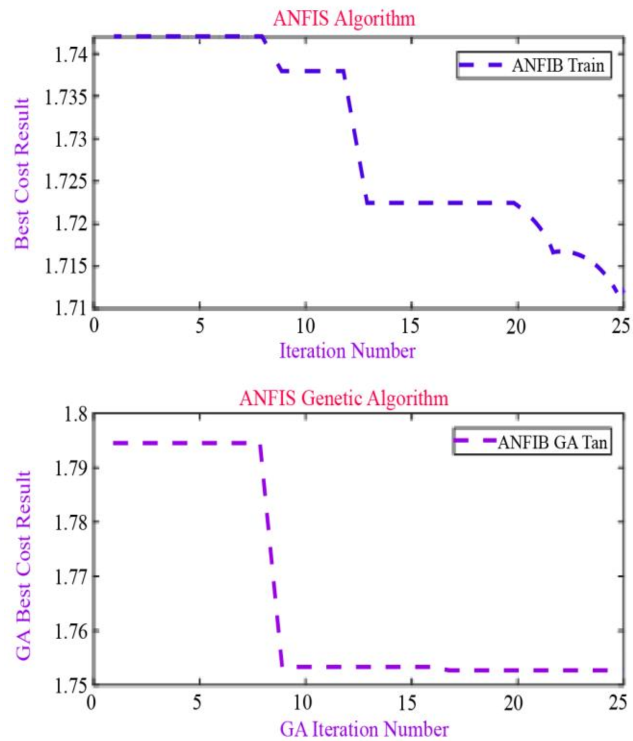

Fig. 10 GA-ANFIS Learning curve

We were able to calculate the metrics accuracy, precision, sensitivity, recall, and specificity as a result of this. Table 5 summarizes the results obtained and confirms the superiority and efficiency of the optimization. In addition, as can be seen in Figure 9, the optimized algorithm converges quickly from the 9th iteration and stabilizes.

On the other hand, the non-optimized algorithm seems to converge quickly from the 8th iteration, but its minimum remains lower than the optimized one. Moreover, it seems difficult to leave the local minimums.

Calculating the metrics from Figures 8, 9, and 10 gives us Table 6 below. This table shows the minimum error, the number of iterations to reach this error, and the performance metrics.

Table 6. Comparison of results between the optimized and non-optimized algorithms

Algorithm	Min lost	Iteration	accuracy	Precision	Sensitivity	Specificity
ANFIS	0.2193	25	79.22	88.01	69.43	94.12
GA-ANFIS	0.0726	8	88.97	89.23	73.20	96.27

In conclusion, GA-ANFIS gives the best results on all aspects of our dataset and can be used as a fault detection algorithm on a complex process like a brewery.

4. Discussion

This study allowed us to validate that production history data and associated failures can be used to predict online failures of a complex industrial system such as a brewery. Combining an ANFIS algorithm with a metaheuristic can optimize the results in terms of time, accuracy, sensitivity, and specificity. This allows for a new way of detecting failures based on daily production data instead of electrical signals, signal processing, and FMEA data on machines, as the authors describe in [21–24]. Comparing our results to those authors, our results seem close to them. These works are summarized in Table 7 below.

Table 7. Comparison of the results of the literature with our own.

Author	Industrial process	Data type	Method	Accuracy
Rajabi, S et al. [21]	industrial rotating equipment	Permutation entropy, signal processing	Multi-output neuro-fuzzy classifier	98.6%
Md Nor, N et al. [22]	chemical process systems	the energy spectrum	Multiscale kernel Fisher discriminant analysis with (ANFIS)	87.02%
Abdelkrim, C [23]	industrial geared motors	600 samples of the vibration signals	Adaptive neuro-fuzzy inference system	95.71%
Verma, A. K [24]	stator winding inter-turn	healthy and faulty three-phase (Current Ia, Ib, Ic) induction motor	Neuro-fuzzy classifier	93.3%
KOMBE, T [25]	Cameroon Breweries	Temperatures in operating modes	AI-PLC Combinatorial Approach ANFIS	79.6 %
Current study	FranceVille Breweries	Production and fault historic	ANFIS-GA	88.97%

We note that our approach based on production data and associated failures has better results compared to the study of temperature data [25] and the energy spectrum [22] of an almost similar chemical industrial system. However, we note that these results are less than those obtained from authors who hybridized their datasets. We probably have an accuracy lower than 90% due to the amount of data (160 days). We think that by increasing the dataset over a decade, our results will be better. This study allows us to consider the development of a tool to help diagnose failures that are not based on sensors and data that are difficult to acquire but rather on the production history that is easy to acquire in third-world industries.

5. Conclusion

Our study aimed to show that production and failure data can be potential candidates for fault classification in a complex system. For this purpose, we extracted production data and related failures from almost one year of production in the brewery industry. To optimize the results, we opted for the ANFIS method, which allowed us to combine the learning capacity of an ANN with the knowledge representation capacity of such systems. The system should work online, and it is important to optimize it to reduce the processing time. For this purpose, AG-ANFIS allowed us to decrease this time by more than 10 times compared to the non-optimized ANFIS algorithm. The results obtained allow us to prove that the extracted features have better results in terms of error and accuracy compared to other types of data. Thus, our dataset, through the optimized algorithm, obtained an MSE of 0.0726, an RMSE of 0.7529, a Mean Error of 0.6281, an STD error of 1.7352, and an accuracy of 88.97%, a precision of 89.23%, a sensitivity of 73.20%, and a specificity of 96.27%. As we said in the section talking about the limitations of this study, this classification rate is not very good, and we are thinking of increasing the dataset to 10 years of data.

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