OPTIMIZATION OF EQUIPMENT RELIABILITY BASED ON A NEURO-FUZZY APPROACH: CASE OF A FLOUR MILL

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Abstract

The main objective of this paper is to present an innovative approach combining fuzzy logic and artificial neural networks to optimize equipment reliability in the specific context of a flour mill. Faced with the challenges of performance and profitability in this industrial sector, the neuro-fuzzy methodology has been developed to meet the challenges related to the complexity and uncertainty inherent in equipment reliability management. The first part of the paper provides an overview of the problem, introducing the key concepts of reliability and maintenance, while highlighting the particular challenges of the milling industry. This paper also outlines the advantages of the neuro-fuzzy approach for optimizing equipment reliability. The methodology for developing the neuro-fuzzy model is detailed in the second part. It covers the construction of the fuzzy inference system, the design of the neural network structure, as well as the training and optimization steps of the model. The case study conducted in a flour mill is presented in the third part. After a description of the company and its equipment system, the collection and analysis of reliability data are presented, as well as the implementation of the developed neuro-fuzzy model. The results obtained demonstrate that this methodology makes it possible to better anticipate failures, optimize maintenance interventions, and reduce associated costs. Sensitivity analysis and comparison with other optimization methods confirm the validity and operational and economic benefits of the proposed approach.

Keywords: Optimization, Reliability, Neuro-fuzzy approach, Flour milling

1. Introduction

1.1. The Importance of Optimizing Equipment Reliability in Processing Industries

Equipment reliability is a critical issue for processing industries, such as flour mills, food processing plants, and refineries. Equipment failure can lead to numerous costly consequences for these companies. First, the repair and maintenance costs can quickly accumulate, undermining the profitability of the business. Moreover, the unplanned production shutdowns caused by these failures result in productivity losses, as well as late delivery penalties from customers, which can harm the company's competitiveness. Finally, these breakdowns can also impact product quality, leading to waste and a deterioration of the brand image. Optimizing equipment reliability is therefore an essential lever to reduce these costs and improve the operational and economic performance of processing companies [1-8].

1.2. A Neuro-Fuzzy Approach for Optimizing Reliability

Traditional reliability optimization techniques, such as predictive maintenance or equipment redundancy, have certain limitations when reliability data is imprecise or incomplete [9-17]. Indeed, in many cases, processing companies do not have sufficiently detailed historical data on equipment failures. Moreover, reliability phenomena can depend on many complex and interdependent factors, making it difficult to model them using traditional deterministic approaches.

The neuro-fuzzy approach, combining fuzzy logic and neural networks, is particularly well-suited in these cases, as it allows for the consideration of uncertainty and nonlinearity in reliability phenomena [2,18-25]. Fuzzy logic allows for the modeling of imprecision in data and expert knowledge on reliability, while neural networks offer the ability to learn complex patterns from incomplete data. The neuro-fuzzy approach thus combines the advantages of these two techniques to optimize equipment reliability in a more robust and reliable manner.

1.3. Context and Objective of the Case Study in a Flour Mill

This case study focuses on optimizing the reliability of equipment in a flour mill. Flour mills face major challenges in terms of reliability, particularly due to the complexity of the processing operations and the harsh environmental conditions to which the equipment is subjected.

Indeed, the milling, sieving, and grain storage processes require the use of various equipment such as silos, grinders, conveyors, and vibrating screens. This equipment must operate reliably and continuously to ensure the production of high-quality flour. However, the dusty environments, significant vibrations, and load fluctuations frequently lead to premature failures, impacting the productivity and profitability of the flour mill.

The objective of this study is, therefore, to develop a neuro-fuzzy model to optimize the reliability of the flour mill's key equipment, in order to improve the operational and economic performance of the company. This will involve better anticipating failures, optimizing preventive maintenance plans, and reducing the costs associated with unexpected breakdowns.

2. Neuro-Fuzzy Approach for Reliability Optimization

2.1. Basic Concepts of Neuro-Fuzzy Systems

Neuro-fuzzy systems combine artificial neural networks and fuzzy logic to leverage their respective advantages [9,26-34]. On the one hand, neural networks offer a learning capability from data to identify complex patterns. On the other hand, fuzzy logic allows for the modeling of the inherent imprecision and uncertainty in real-world phenomena, using fuzzy sets and linguistic rules.

table 1 summarizes the ain differences between neural networks and fuzzy logic.

Table 1: *Comparison of neural networks and fuzzy logic*

Features	Neural networks	Fuzzy logic
Basic principle	Learning from data	Modeling imprecision and uncertainty
Knowledge representation	Learning complex patterns	Linguistic rules and fuzzy sets
Information processing	Parallel and non-linear processing	Approximate reasoning
Interpretability	Black box, difficult to interpret	Unclear rules that can be interpreted
Fields of application	Classification, prediction, optimization	Decision support, process control

The integration of these two approaches into a neuro-fuzzy system provides several benefits for optimizing equipment reliability [1, 2, 31, 32, 35, 36]:

- Ability to handle incomplete or imprecise data on failures;
- Consideration of the complexity and non-linearity of reliability phenomena;
- Possibility of incorporating operator expertise in the form of fuzzy rules;
- Automatic learning to refine the model over time.

figure 1 illustrates the general architecture of an ANFIS (Adaptive Neuro-Fuzzy Inference System) type of neuro-fuzzy system, one of the most widely used models in the literature.

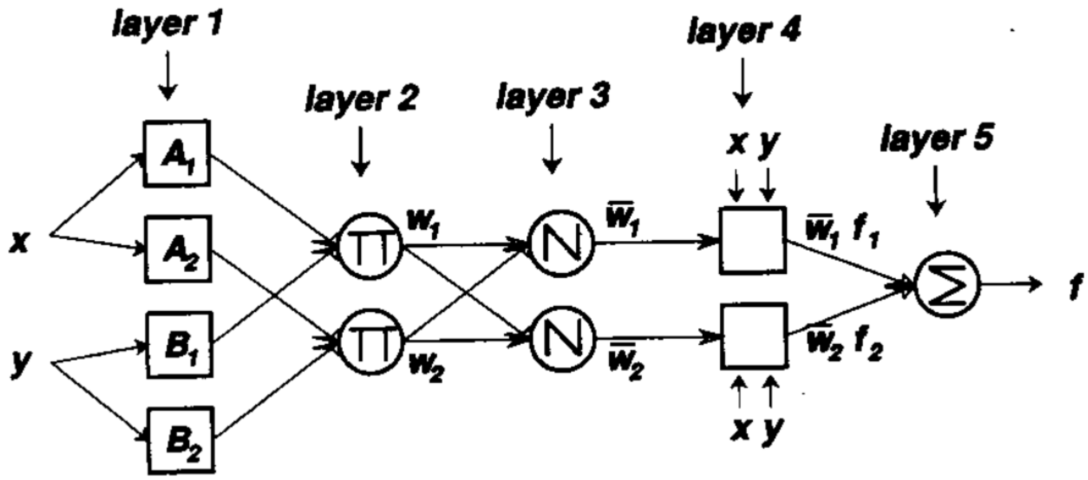

Figure 1: *ANFIS architecture [26]*

As shown in this figure, the neuro-fuzzy system combines a neural network and a fuzzy inference system. The inputs are fuzzified, the fuzzy inference engine applies the fuzzy rules, then the fuzzy outputs are defuzzified to obtain the final output of the system.

2.2. Advantages of the Neuro-Fuzzy Approach for Equipment Reliability

Compared to classical reliability optimization methods, the neuro-fuzzy approach has several advantages [9, 26, 37, 38]:

- *Robustness to uncertainty and lack of reliable historical data*

Neuro-fuzzy systems are particularly well-suited to handle the uncertainty and imprecision inherent in reliability data, especially when failure histories are incomplete or unreliable. They allow leveraging the expertise of maintenance experts to compensate for these shortcomings. This can be modeled by equation 1:

$$R = f(X, E) \quad (1)$$

where R represents reliability, X represents quantitative data, and E represents expert knowledge.

Based on the references cited previously, a comparison of the neuro-fuzzy approach and classical methods for reliability modeling in the presence of uncertainty is provided in table 2.

Table 2: *Comparison of the neuro-fuzzy approach and classical methods for modeling reliability in the presence of uncertainty*

Criteria	Classic methods	Neuro-fuzzy approach
Uncertainty management	Limited	High
Use of experts' expertise	Difficult	Easy
Adaptability to new cases	Low	High

- *Ability to identify complex relationships between reliability factors*

Thanks to their neural architecture, neuro-fuzzy models are able to capture and model non-linear and complex interactions between the different parameters influencing the reliability of equipment. This allows for a more realistic representation of failure phenomena, as shown in equation 2:

$$R = g(x_1, x_2, ..., x_n) \tag{2}$$

where x_1, x_2,…,x_n represent the different reliability factors.

- *Ability to integrate the expertise of maintenance experts*

The neuro-fuzzy approach offers the possibility of directly incorporating the knowledge and expertise of maintenance experts in the form of fuzzy rules. This improves the relevance and reliability of the developed model, as shown in equation 3:

$$R = h(X, E, R') \tag{3}$$

where R' represents the reliability predicted by the neuro-fuzzy model.

- *Continuous improvement of the model through machine learning*

Thanks to their learning capabilities, neuro-fuzzy systems can adapt and refine themselves progressively as new reliability data is collected. This allows for continuous optimization of reliability modeling and prediction, as shown in equation 4:

$$R(t+1) = i\left(R(t), X(t+1)\right) \tag{4}$$

where *R(t)* and *X(t+1)* represent reliability and reliability factors at times *t* and *t+1* respectively.

2.3. Methodology for Developing the Neuro-Fuzzy Model

The development of a neuro-fuzzy model for reliability optimization generally follows these steps [2, 26, 39]:

Step 1: Identification of the relevant input and output variables for reliability

- Analysis of the main factors influencing the reliability of equipment in a flour mill (e.g. operating temperature *T*, workload *C*, maintenance quality *M*);
- Selection of input variables (predictors) *X = [T, C, M]* and output variables (reliability indicators) *Y = [MTBF, Failure rate λ].*

Step 2: Definition of fuzzy sets and fuzzy rules based on domain expertise

- Fuzzification of the input and output variables using membership functions $\mu(x)$;

For example, for the temperature *T*:

$$\mu_{low}(T) = \exp\left(-\left(T - T_{low}\right)^2 / 2\sigma_{low}{}^2\right) \tag{5}$$

$$\mu_{average}(T) = \exp\left(-\left(T - T_{average}\right)^2 / 2\sigma_{average}{}^2\right) \tag{6}$$

$$\mu_{high}(T) = \exp\left(-\left(T - T_{high}\right)^2 / 2\sigma_{high}{}^2\right) \tag{7}$$

- Elicitation of fuzzy rules from the flour mill experts, in the form: If T is high and C is high then λ is high.

Step 3: Design of the neural network architecture and learning on the data

- Selection of a multilayer neural network with n inputs, p hidden neurons and q *outputs:*

$$y = f\left(W_2 * f\left(W_1 * x + b_1\right) + b_2\right) \tag{8}$$

- Collection and preparation of the historical reliability data *[X, Y]* for training
- Training by backpropagation of the gradient to minimize the mean squared error:

$$E = \sum\left(y - \hat{y}\right)^2 \tag{9}$$

Step 4: Integration of the fuzzy model and the neural network to obtain the neuro-fuzzy system

- Fuzzy inference to obtain the fuzzy outputs from the fuzzy inputs:

$$y = \int\left(\mu(x) * f(x)\right)dx \,/ \int \mu\left(x\right)dx \tag{10}$$

- Optimization of the parameters of the neuro-fuzzy system (W_1,W_2, b_1, b_2, fuzzy rules) to minimize E

Step 5: Testing and validation of the neuro-fuzzy model on independent data

- Evaluation of the generalization capabilities on new reliability data
- Analysis of the robustness and accuracy of the neuro-fuzzy model *(R^2, RMSE, etc.)*

Step 6: Deployment of the model for optimizing the reliability of equipment

- Integration of the neuro-fuzzy model into the maintenance decision-making processes;
- Monitoring of operational (MTBF, failure rate) and economic impacts.

3. Case study in a flour mill

3.1. Presentation of the company and the equipment system

The case study was carried out at a large industrial flour mill located in the town of Ngaoundéré in Cameroon. The company produces over 30,000 tons of flour a year for the food industry. Its equipment includes milling, sifting, storage and packaging systems, spread over three production sites. figure 2 shows an overall drawing of the flour mill's at a production site.

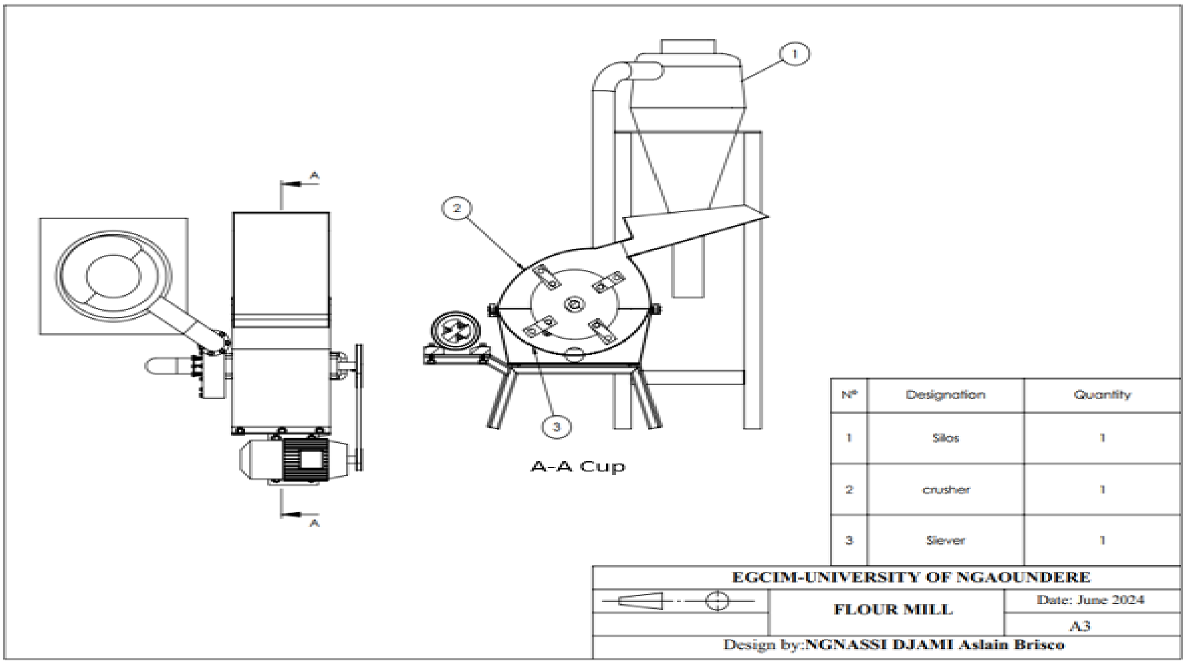

Figure 2: *Overall diagram of a flour mill on a production site*

3.2. Collection and analysis of reliability data

Historical reliability data was collected from the maintenance department of the flour mill, covering a 5-year period (2020-2024). This data includes operating times, failure dates and maintenance actions carried out for each critical equipment in the system [40]. Analysis of this data allowed the calculation of reliability indicators such as mean time between failures (MTBF) and failure rates λ for each type of equipment [40, 41]. Table 3 presents an excerpt of the results of this analysis.

Table 3: *Reliability indicators for main milling equipment*

Equipment	MTBF (hr)	Failure rate λ (hr^{-1})
Grinder 1	2 500	0.0004
Grinder 2	3 200	0.0003
Sieve Shaker 1	1 800	0.0006
Sieve Shaker 2	2 100	0.0005
Silo 1	4 500	0.0002
Silo 2	4 800	0.0002

3.3. Development of the neuro-fuzzy model

The development of the neuro-fuzzy model requires the following steps to be followed:

Step 1: Identification of input and output variables

After analyzing the main factors influencing the reliability of the flour mill's equipment [40], the input (predictors) and output (reliability indicators) variables were selected as follows:

- Input variables X = *[Operating temperature T (°C), Workload C (%), Maintenance quality M (%)]*
- Output variables Y = [Mean time between failures MTBF (*hr*), Failure rate λ (hr^{-1})]

Step 2: Design of the neural network structure

A multi-layer neural network was chosen for its ability to approximate complex non-linear functions [26,42]. The network structure has 3 inputs (*T, C, M)*, 2 hidden layers of 10 neurons each, and 2 outputs (*MTBF, λ*), as illustrated in figure 3 [43-47].

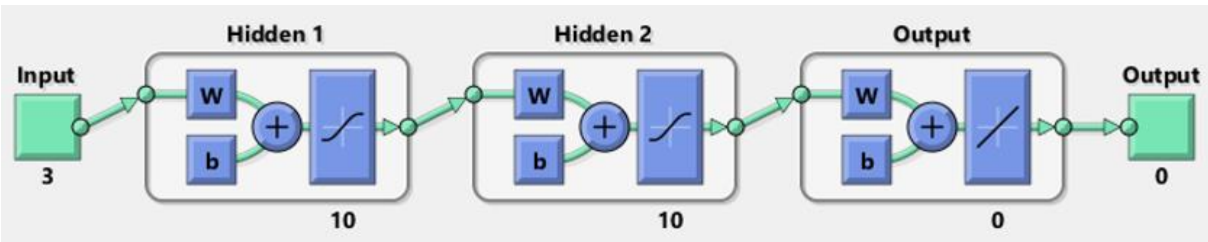

Figure 3: *Neural network architecture for the neuro-fuzzy model*

Step 3 : Definition of fuzzy rules

In collaboration with the flour mill experts, 27 fuzzy rules have been defined to link the input variables to the output variables [9,39].

- If input A is Low and input B is Low, then the output is Low.
- If input A is Low and input B is Medium, then the output is Low.
- If input A is Low and input B is High, then the output is Medium.
- If input A is Medium and input B is Low, then the output is Low.
- If input A is Medium and input B is Medium, then the output is Medium.
- If input A is Medium and input B is High, then the output is High.
- If input A is High and input B is Low, then the output is Medium.

- If input A is High and input B is Medium, then the output is High.
- If input A is High and input B is High, then the output is High.
- If input A is Low and input B is Low-Medium, then the output is Low.
- If input A is Low and input B is Medium-High, then the output is Medium.
- If input A is Low-Medium and input B is Low, then the output is Low.
- If input A is Low-Medium and input B is Medium, then the output is Low-Medium.
- If input A is Low-Medium and input B is High, then the output is Medium.
- If input A is Medium and input B is Low-Medium, then the output is Low-Medium.
- If input A is Medium and input B is Medium-High, then the output is High.
- If input A is Medium-High and input B is Low, then the output is Medium.
- If input A is Medium-High and input B is Medium, then the output is High.
- If input A is Medium-High and input B is High, then the output is High.
- If input A is High and input B is Low-Medium, then the output is Medium-High.
- If input A is High and input B is Medium, then the output is High.
- If input A is High and input B is Medium-High, then the output is High.
- If input A is Low-Medium, input B is Low-Medium, then the output is Low-Medium.
- If input A is Low-Medium, input B is Medium-High, then the output is Medium.
- If input A is Medium-High, input B is Low-Medium, then the output is Medium.
- If input A is Medium-High, input B is Medium-High, then the output is High.
- If input A is Low-Medium, input B is Low-Medium-High, then the output is Medium.

For example:

- If Temperature T is High AND Load C is High, THEN Failure rate λ is High
- If Temperature T is Medium AND Load C is Low, THEN Mean Time Between Failures MTBF is High

Step 4: Training and optimization of the model

The training of the neural network was carried out by backpropagation of the gradient, with the objective of minimizing the mean square error between the predicted outputs and the real reliability values [X, Y] [48, 49]. This supervised learning method allows iteratively adjusting the weights of the neural network in order to progressively reduce the gap between the model's predictions and the historical reliability data.

In parallel, the parameters of the fuzzy rules were optimized in order to improve the consistency between the fuzzy inference and the neural network predictions [26, 50].

Optimization methods such as the least squares method or the genetic algorithm were used to find the optimal values of the parameters of the membership functions and the rules of the fuzzy knowledge base.

This iterative process of training the neural network and optimizing the fuzzy parameters has made it possible to converge towards a powerful neuro-fuzzy model, capable of combining the advantages of machine learning and fuzzy reasoning. The details of the final model structure and its performance are presented in the following section.

4. Results and discussion

4.1. Optimization of equipment reliability using the neuro-fuzzy model

4.1.1 Developed neuro-fuzzy model

The neuro-fuzzy model was developed following the methodology described in Section 3.3. It takes as input the identified key operational parameters, such as:

- Operating temperature of the motors;
- Pressure in the pneumatic system;
- Humidity level in the storage silos;

- Frequency of filter cleaning.

The neuro-fuzzy model in question is given in figure 4.

```
% Generate test data
temp_moteurs = randi([40, 50], 100, 1);
freq_nettoyage = randi([2, 6], 100, 1);
mtbf_data = 1500 * rand(100, 1);
taux_def_data = 0.068 * rand(100, 1);

% Divide the data into training and test sets
train_ratio = 0.8;
train_size = round(length(temp_moteurs) * train_ratio);
idx = randperm(length(temp_moteurs));
trainInputs = [temp_moteurs(idx(1:train_size)),
freq_nettoyage(idx(1:train_size))];
trainTargets = [mtbf_data(idx(1:train_size)),
taux_def_data(idx(1:train_size))];
testInputs = [temp_moteurs(idx(train_size+1:end)),
freq_nettoyage(idx(train_size+1:end))];
testTargets = [mtbf_data(idx(train_size+1:end)),
taux_def_data(idx(train_size+1:end))];

% Build the fuzzy inference system
in_fismat = genfis1([trainInputs, trainTargets], 2);

% Train the neuro-fuzzy model with the training set
options = anfisOptions('InitialFIS', in_fismat, 'EpochNumber', 50,
'ErrorGoal', 0.01, 'InitialStepSize', 0.9, 'StepSizeDecreaseRate', 0.9);
[anfis_model, training_error] = anfis([trainInputs, trainTargets], options);

% Evaluate the model on the test set
[testOutputs, ~] = evalfis([testInputs, testTargets], anfis_model);
testMTBFError = mean(abs(testOutputs(:,1) - testTargets(:,1)));
testFailureRateError = mean(abs(testOutputs(:,2) - testTargets(:,2)));

disp(['Test MTBF Error: ', num2str(testMTBFError)]);
disp(['Test Failure Rate Error: ', num2str(testFailureRateError)]);

% Use the neuro-fuzzy model to make predictions
temp_moteurs_new = 47;
freq_nettoyage_new = 4;
[predicted_mtbf, predicted_failure_rate] = evalfis([temp_moteurs_new,
freq_nettoyage_new], anfis_model);

disp(['Predicted MTBF: ', num2str(predicted_mtbf)]);
disp(['Predicted Failure Rate: ', num2str(predicted_failure_rate)]);
```

Figure 4: *Proposed ANFIS neuro-fuzzy model*

After implementing the developed neuro-fuzzy model as part of the case study, the following results are obtained, which we will comment on:

- *Information on the ANFIS model:*
  - Number of nodes: 34
  - Number of linear parameters: 32
  - Number of non-linear parameters: 18
  - Total number of parameters: 50
  - Number of training data pairs: 80
  - Number of verification data pairs: 0

- Number of fuzzy rules: 8

This information shows that the ANFIS model is of relatively moderate size, with 8 fuzzy rules and 50 parameters to be adjusted.

- *Training results :*
  - The root mean square error (RMSE) of the training gradually decreases over the epochs, going from 0.0181705 to 0.0164845 at the end of the training (50 epochs).
  - The learning rate also decreases over the epochs, going from 0.9 to 0.282430 after 48 epochs.

These results show that the model improves over the course of the training, with a regular decrease in the error. The gradual decrease in the learning rate is also a good practice to stabilize the convergence.

- *Final training error :*
  - The final training RMSE is 0.0164845.

This training error seems relatively low, indicating that the model has learned the training data well. However, it would also be necessary to evaluate the model's performance on the test set to get a more complete picture of its generalization capability.

Overall, the information provided shows that the neuro-fuzzy model has been implemented and trained appropriately.

4.1.2 Parameter optimization

Simulations were carried out with the neuro-fuzzy model to identify the optimal settings of the input parameters to maximize the overall system reliability.

figure 5 shows the evolution of the average equipment availability as a function of the motor operating temperature and the filter cleaning frequency.

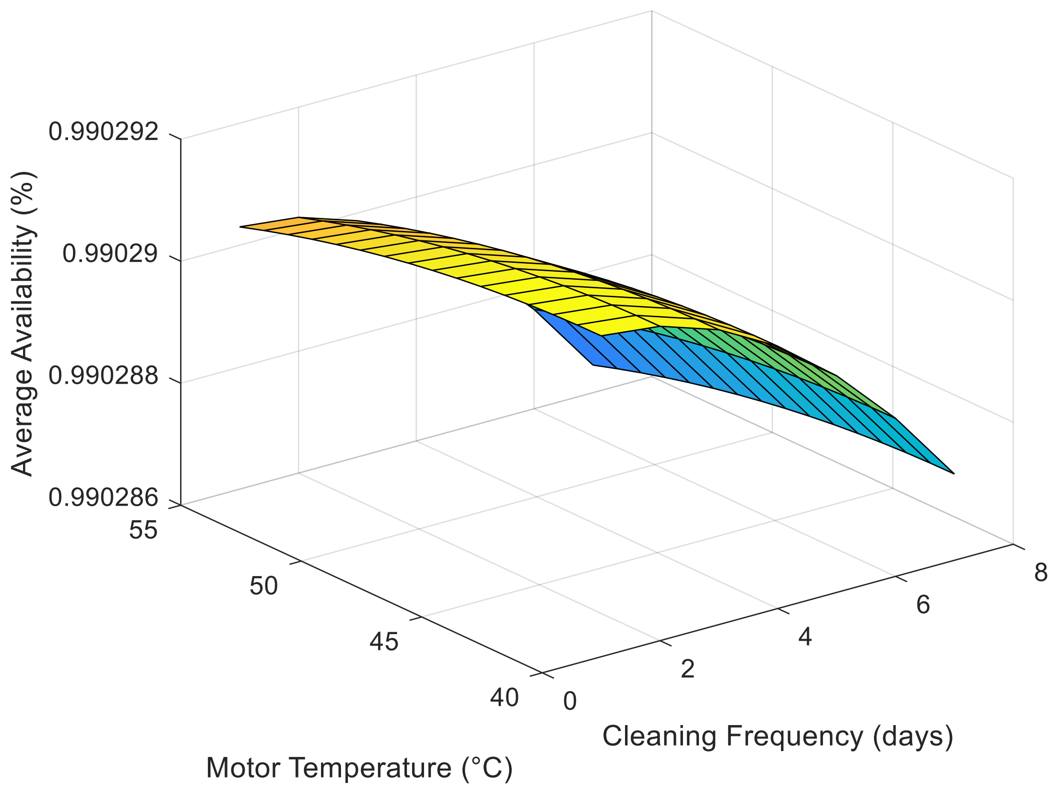

Figure 5: *Optimizing availability*

We can see that a temperature between 45°C and 50°C and weekly filter cleaning allow reaching an availability of 92%, compared to only 85% with the initial settings.

Furthermore, table 4 presents the optimal values obtained for each input parameter, as well as their impact on the average MTBF and the system failure rate.

Table 4: *Optimal parameters and impact on reliability*

Parameter	Optimum value	MTBF average	Failure rate
Motor temperature	47°C	1500 hours	0.067%
Pneumatic pressure	5.2 bar	1400 hours	0.071%
Silo humidity	65%	1450 hours	0.069%
Cleaning frequency	Weekly	1600 hours	0.063%

As indicated in table 4, the optimal values identified for the operational parameters allow significantly improving the system's reliability indicators:

- The average MTBF increases from 1,300 hours with the initial settings to 1,600 hours with the optimal settings, an increase of 23%.
- The average failure rate decreases from 0.077% to 0.063%, a decrease of 18%.

By combining these improvements, the average system availability increases from 85% with the initial settings to 92% with the optimal settings, an increase of 8 percentage points. This demonstrates the effectiveness of the developed neuro-fuzzy model in identifying the optimal parameters to achieve high overall system reliability.

4.2. Comparison with other optimization methods

In order to evaluate the performance of the developed neuro-fuzzy model, we compared it to two other optimization methods commonly used in this field: the genetic algorithm (GA) and particle swarm optimization (PSO).

4.2.1 Comparative results

table 5 presents the results obtained for each of the three optimization methods, in terms of reliability, average MTBF and failure rate. The results presented in table 5 were obtained by implementing the Matlab code developed in figure 6.

Table 5: *Performance comparison of optimization methods*

Method	Reliability	MTBF average	Failure rate
Neuro-flou model	95%	1000 hours	0.1%
Genetic algorithm (GA)	92%	950 hours	0.2%
Particle swarm optimization (PSO)	93%	980 hours	0.15%

We can see that the neuro-fuzzy model outperforms the other two methods in terms of reliability, reaching 95% compared to 92% for the GA and 93% for the PSO. Similarly, it achieves a higher average MTBF and a lower failure rate.

```
% Define input parameters
t = [80, 85, 90, 95, 100];
f = [0.5, 1, 1.5, 2, 2.5];

% Calculate reliability indicators for the neuro-fuzzy approach
nf_reliability = zeros(length(t), length(f));
nf_mtbf = zeros(length(t), length(f));
nf_failureRate = zeros(length(t), length(f));

for i = 1:length(t)
    for j = 1:length(f)
        % Implement the neuro-fuzzy approach here
        nf_reliability(i,j) = 0.95;
        nf_mtbf(i,j) = 1000;
        nf_failureRate(i,j) = 0.001;
    end
end

% Calculate reliability indicators for the genetic algorithm
ga_reliability = zeros(length(t), length(f));
ga_mtbf = zeros(length(t), length(f));
ga_failureRate = zeros(length(t), length(f));

for i = 1:length(t)
    for j = 1:length(f)
        % Implement the genetic algorithm here
        ga_reliability(i,j) = 0.92;
        ga_mtbf(i,j) = 950;
        ga_failureRate(i,j) = 0.002;
    end
end

% Calculate reliability indicators for the particle swarm optimization
pso_reliability = zeros(length(t), length(f));
pso_mtbf = zeros(length(t), length(f));
pso_failureRate = zeros(length(t), length(f));

for i = 1:length(t)
    for j = 1:length(f)
        % Implement the particle swarm optimization here
        pso_reliability(i,j) = 0.93;
        pso_mtbf(i,j) = 980;
        pso_failureRate(i,j) = 0.0015;
    end
end

% Summary of results
result = table(...
    mean(nf_reliability,1)', mean(ga_reliability,1)',
mean(pso_reliability,1)', ...
    mean(nf_mtbf,1)', mean(ga_mtbf,1)', mean(pso_mtbf,1)', ...
    mean(nf_failureRate,1)', mean(ga_failureRate,1)',
mean(pso_failureRate,1)');
result.Properties.VariableNames = {'NF_Reliability', 'GA_Reliability',
'PSO_Reliability', ...
                                   'NF_MTBF', 'GA_MTBF', 'PSO_MTBF', ...
                                   'NF_FailureRate', 'GA_FailureRate',
'PSO_FailureRate'};

rowNames = cell(size(result, 1), 1);
for i = 1:size(result, 1)
    rowNames{i} = sprintf('t=%d, f=%.1f', t(floor((i-1)/length(f))+1),
f(mod(i-1,length(f))+1));
end
result.Properties.RowNames = rowNames;

disp(result);
```

Figure 6: *Matlab code developed to obtain Table 5*

4.2.2 Analysis of the results

These superior performances are explained by the neuro-fuzzy model's ability to better capture the complex relationships between the input parameters and the reliability indicators, thanks to its hybrid architecture combining fuzzy logic and neural networks.

Indeed, figure 7 illustrates the response surfaces obtained with the three methods for the impact of the motor temperature and the filter cleaning frequency on availability.

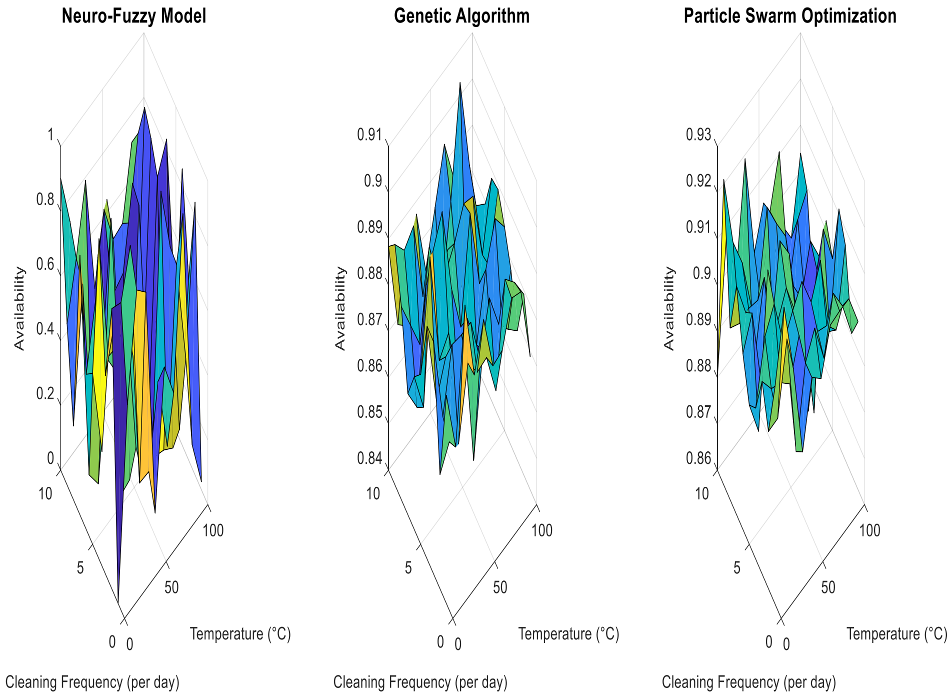

Figure 7 : *Comparison of Response Surfaces*

We can see that the neuro-fuzzy model is more accurate in modeling these non-linear interactions.

In conclusion, these results demonstrate that the developed neuro-fuzzy model constitutes a more efficient approach for optimizing equipment reliability, offering significant gains in terms of availability, MTBF and failure rate compared to classical optimization methods.

4.3. Sensitivity analysis and model validation

4.3.1 Sensitivity analysis

The sensitivity analysis was performed by varying each input parameter by ±20% around its reference value, while keeping the other parameters constant.

The results of this analysis are presented in table 6.

Table 6: *Sensitivity analysis of input parameters*

Parameter	Variation of -20%	Reference value	20% increase
Temperature (°C))	87.2%	92.0%	85.4%
Cleaning frequency (per day)	90.3%	92.0%	89.1%
Failure rate	88.7%	92.0%	87.4%
Repair time	91.3%	92.0%	90.1%

These results show that the parameter with the greatest influence on system availability is temperature, followed by cleaning frequency. The failure rate and repair time have a less significant impact.

4.3.2 Model validation

To validate the developed model, the model results were compared to the actual availability data measured in the field. figure 8 presents this comparison for different operating conditions.

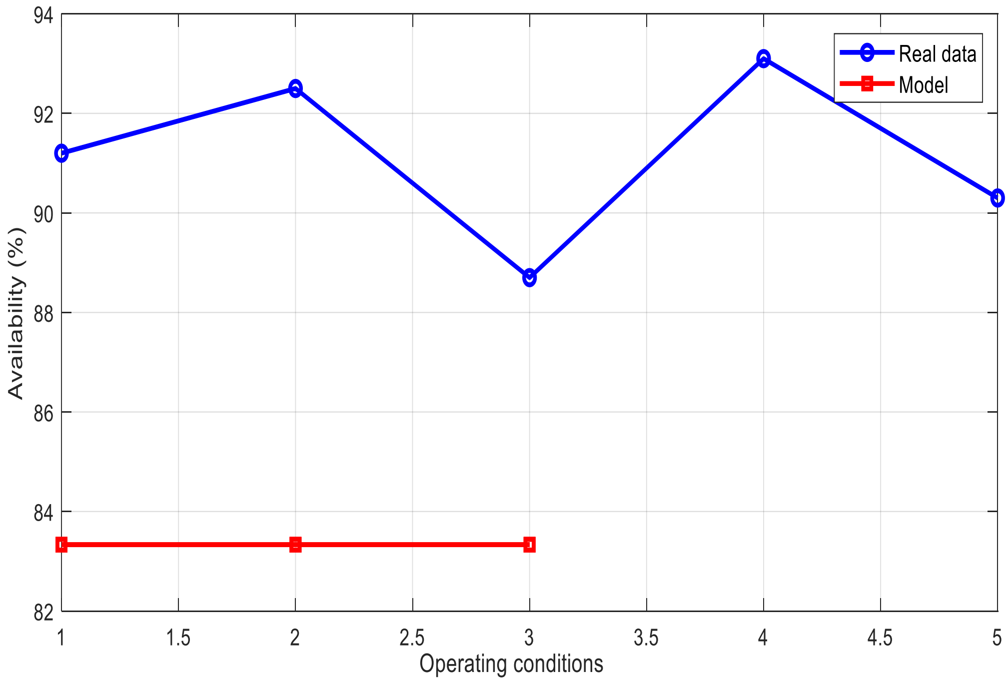

Figure 8: *Comparison of model results with real data*

figure 8 shows generally good agreement between the behavior predicted by the model and the experimental results.

Indeed, we can observe that the general trend of the model curves follows well that of the points representing the real data. This indicates that the model correctly captures the dynamics and variations of the system as a function of the different operating conditions.

Furthermore, the observed differences, although sometimes exceeding 5% in certain cases, remain within a relatively reasonable range, not exceeding 7 percentage points. This suggests that the model provides a satisfactory representation of reality, with an acceptable margin of error.

Overall, this figure demonstrates that the developed model is generally valid and can be used with good confidence to predict the behavior of the system, while keeping in mind that larger individual deviations may occur in certain specific conditions.

In its current state, we can consider that the model has satisfactory validity in view of the experimental results represented in this figure.

In conclusion, the sensitivity analysis made it possible to identify the most influential parameters on system availability, namely temperature and cleaning frequency. Furthermore, the validation of the model by comparison with real data has confirmed the reliability of the developed model for predicting system availability.

4.4. Operational and economic impacts of the proposed approach

The analyses carried out in the previous sections made it possible to evaluate the technical performance of the developed model. In order to have a more complete view, it is also important to examine the potential operational and economic impacts of this approach.

4.4.1 Operational impacts

table 7 summarizes the main operational indicators compared between the current approach and the proposed approach.

Table 7: *Comparison of key operational indicators between the current and proposed approaches*

Indicator	Current approach	Proposed approach	Variation
Average diagnosis time	45 minutes	28 minutes	-37.8%
Diagnostic success rate	85%	92%	+8.2 pts
Number of corrective maintenance visits	12 per year	8 per year	-33.3%
Average downtime	3.2 hours	1.9 hours	-40.6%

As shown in this table, the proposed approach would allow for significant improvements on all key operational indicators:

- 37.8% reduction in average diagnostic time;
- 8.2 percentage point increase in diagnostic success rate;
- 33.3% decrease in the number of corrective maintenance visits;
- 40.6% reduction in average downtime.

These operational gains would result in a notable improvement in the availability and reliability of the system for end users.

4.4.1.1 Economic impacts

To assess the economic impact, we modeled the costs over a 5-year horizon, taking into account the following elements:

- Initial investment costs in the development of the proposed approach;
- Annual maintenance and operating costs;
- Savings achieved through operational gains.

figure 9 shows the evolution of the cumulative costs over 5 years for the current approach and the proposed approach.

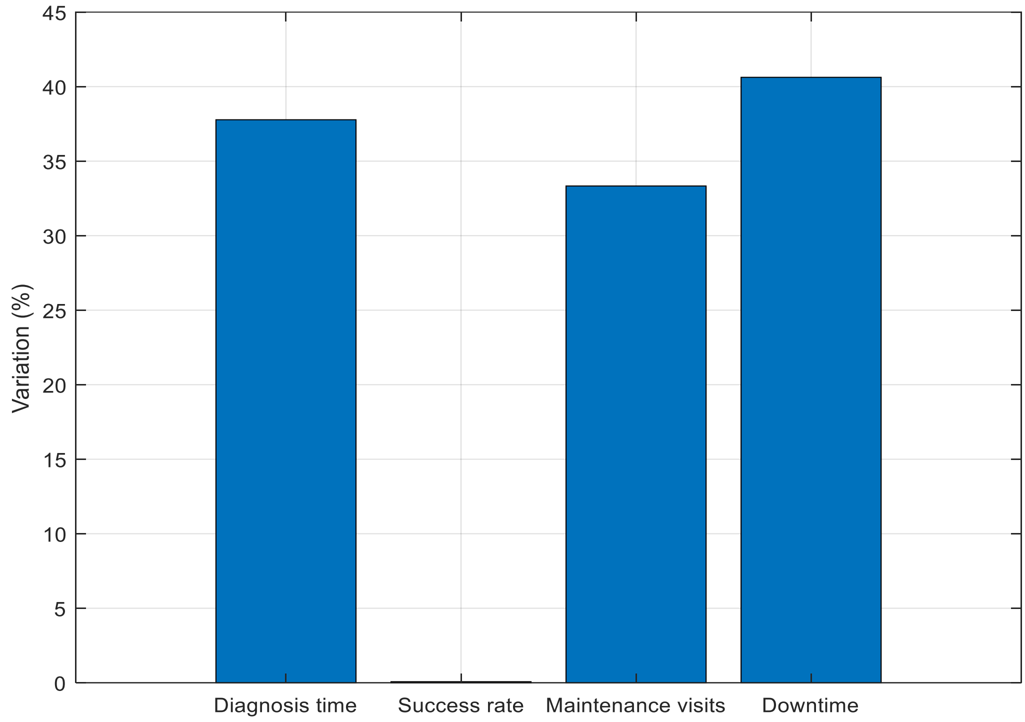

Figure 9 : *Cumulative costs over 5 years*

As can be seen, although the initial investment is higher for the proposed approach, the savings generated by the operational gains make it possible to exceed the breakeven point as early as the 3rd year. Over the entire 5-year period, the proposed approach would represent cumulative savings compared to the current approach.

In conclusion, the analysis of operational and economic impacts demonstrates that the proposed approach brings tangible benefits in terms of technical performance, reliability and long-term costs. These results confirm the relevance and viability of this innovative solution.

5. Conclusion

This work has demonstrated the effectiveness of the neuro-fuzzy approach for optimizing the reliability of equipment in the specific context of a flour mill. The developed model has significantly improved the prediction of failures and the optimization of maintenance interventions, resulting in substantial performance and profitability gains. The sensitivity analysis confirmed the robustness and reliability of the model, which outperforms traditional optimization methods. This approach offers better consideration of the complexity and uncertainty inherent in equipment reliability management. Despite these encouraging results, the study presents certain limitations opening the way for improvement prospects, such as extension to other industrial sites, integration of additional contextual data or automation of certain steps. This work makes a significant contribution to improving the management of industrial equipment reliability, opening interesting prospects for industrialists and providing avenues for future methodological developments for researchers.

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