IMPLEMENTATION OF A RULE-BASED EXPERT SYSTEM TO SUPPORT COMPRESSOR MAINTENANCE

BY

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ABSTRACT

Industrial compressors are essential equipment in sectors such as oil and gas, refrigeration, mining, energy, and manufacturing, where operational continuity and equipment reliability are critical. Due to severe operating conditions involving high pressure and temperature, compressors are susceptible to mechanical failures, wear, and performance degradation. Consequently, efficient maintenance strategies are required to minimize downtime and reduce operational costs. This study presents the implementation of a Rule-Based Expert System to support compressor maintenance by assisting technicians and mechanics in fault diagnosis and corrective decision-making. Knowledge acquisition was performed through questionnaires administered to compressor maintenance specialists, enabling the collection of information related to symptoms, causes, and maintenance procedures. The acquired knowledge was represented through production rules and structured using decision tables to facilitate logical organization and validation. The expert system was developed using Exsys Corvid, a knowledge-based system development environment. System validation was conducted using Cohen's Kappa coefficient to measure the level of agreement between the system's recommendations and expert evaluations. The obtained results indicate a moderate level of agreement ($\kappa = 0.50$), demonstrating that the proposed system provides consistent diagnostic recommendations and can effectively support maintenance decision-making processes. The study confirms the applicability of rule-based expert systems as a practical and interpretable solution for supporting preventive and corrective maintenance activities in industrial compressors.

Keywords: Artificial Intelligence, Expert System, Compressor Maintenance, Rule-Based System, Decision Table, Exsys Corvid.

1. INTRODUCTION

Industrial compressors play a fundamental role in various sectors, such as oil and gas, refrigeration, the food industry, mining, energy, and manufacturing. These devices are responsible for the compression and circulation of gases or compressed air, and are essential for the continuous operation of industrial processes. However, due to continuous operation and high pressure and temperature conditions, compressors are subject to mechanical wear, operational failures, and efficiency losses.

In this context, compressor maintenance systems emerge as important tools for monitoring, fault diagnosis, preventive maintenance, and predictive maintenance of equipment. With the evolution of artificial intelligence and expert systems, several intelligent solutions have been developed to support technicians and engineers in decision-making related to industrial maintenance.

One of the first systems used to support the maintenance of compression systems was Frigexpert, developed by the Centre d'Énergétique of the École des Mines de Paris in 1991. This expert system was created for the diagnosis and maintenance of compression refrigeration systems, using sensors and logical inference rules to identify operational failures.

During the same period, the Expert System for Maintenance of One-Stage Compression Refrigerating Systems, developed by CLODIC – École des Mines de Paris in 1991, was designed to support the maintenance of single-stage compression refrigerant systems. The system used analysis of operational parameters and production rules to detect faults and recommend corrective actions.

Another important system was the VP-Expert Industrial Maintenance System, developed by Brian Sawyer in 1987. VP-Expert was widely used in the construction of industrial expert systems applied to the maintenance of machines and compressors through IF...THEN type rules.

Later, in 2012, Heinz P. Bloch developed the Compressor Reliability and Maintenance Expert System, focused on operational reliability and intelligent maintenance of industrial compressors. The system allowed vibration analysis, identification of mechanical failures, and monitoring of equipment performance.

With the advancement of Industry 4.0 and artificial intelligence, modern predictive maintenance systems have emerged. The Compressor Predictive Maintenance System, developed by Alessandro Costa, Emilio Mastriani, Federico Incardona, Kevin Munari, and Sebastiano Spinello in 2024, stands out, using intelligent sensors, artificial intelligence algorithms, and automatic fault classification techniques to predict operational problems before serious failures occur. In the same year, Bogdan Łobodziński (2024) developed the Predictive Maintenance Solution for Reciprocating Compressors system, based on industrial data analysis and continuous monitoring of critical components of reciprocating compressors.

2. THEORETICAL FOUNDATION

Artificial Intelligence

The theoretical foundation of this work was based on the concepts of Artificial Intelligence, Expert Systems, industrial maintenance, compressors, rule-based systems, and decision tables, drawing on authors such as John McCarthy (1956), Edward Feigenbaum (1970), John Moubray (1997), Heinz P. Bloch (2012), and Morton A. Harrison (1965).

Artificial Intelligence (AI) is a branch of computer science dedicated to developing systems capable of simulating human reasoning, learning, solving problems, and making decisions automatically.

According to John McCarthy (1956), Artificial Intelligence is "the science and engineering of making intelligent machines." The term was officially introduced during the Dartmouth Conference in 1956, considered the starting point of modern AI.

Expert System

Expert Systems are a practical application of Artificial Intelligence, developed to emulate the decision-making capacity of experts in a given activity.

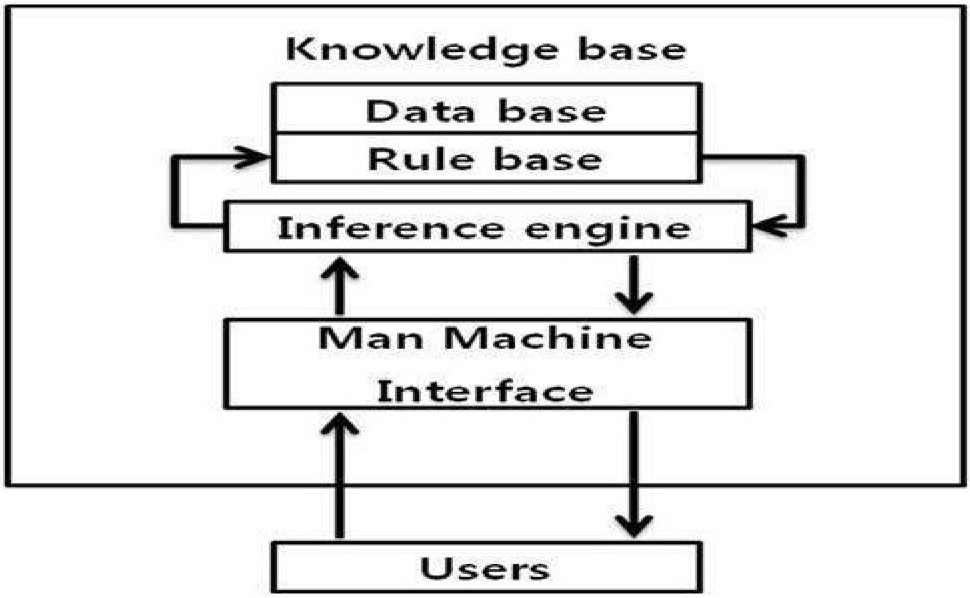

Figure 1. Structure of rule based expert system.
Source(Giarrantano,1994)

The knowledge base is the component where knowledge about the problem is implemented in an appropriate computational form. Among the most commonly applied knowledge techniques are: rules, objects, and semantic networks. Knowledge is considered heuristic in nature, consisting of practical rules or empirical procedures resulting from years of experience. The inference engine performs the processes necessary to arrive at a solution, from a set of initial data. The working memory, in turn, stores the relevant information about the problem. Finally, the user interface allows interaction between the user and the Expert System.

The objectives of expert systems are to automate and assist in solving problems, documenting the knowledge necessary for their solution. By allowing increased availability and permanence of knowledge of the activity addressed (Giarrantano; Riley, 1994). ESs can be used as a means to promote knowledge management in an organization. Artificial Intelligence is recognized as an important source of contributions in the development of techniques and computational systems for knowledge management in companies (Smith, Farquhar, 2000).

Maintenance

Maintenance consists of the set of activities aimed at preserving or restoring equipment to proper operating conditions.

According to John Moubray (1997), modern maintenance has evolved from a corrective approach to preventive and predictive strategies, using intelligent technologies to reduce failures and increase operational reliability.

Compressor

Compressors are machines used to increase the pressure of gases or compressed air, being widely used in industrial processes, refrigeration, oil and gas, mining and pneumatic systems.

According to Bloch (2012), industrial compressors play a fundamental role in production systems, requiring continuous monitoring and efficient maintenance due to the high operating conditions of pressure and temperature.

According to Heinz P. Bloch (2012), compressor failures can cause:

production interruptions;

financial losses;

reduced energy efficiency;

operational risks.

Therefore, intelligent maintenance techniques have been used for the diagnosis and prevention of failures in industrial compressors.

Rule-Based Systems

Rule-based systems represent knowledge through IF...THEN type production rules, allowing for automatic inferences.

According to Edward Feigenbaum (1970), production rules constitute one of the most natural forms of representing human knowledge in expert systems.

According to Pannu (2015), rule-based systems have advantages such as:

simplicity;

interpretability;

ease of maintenance;

automatic decision-making capability.

These techniques are widely used in:

industrial diagnostics;

intelligent maintenance;

medical systems;

decision support.

Decision Table

A decision table is a technique used to represent logical combinations between conditions and actions in decision-making processes.

According to Morton A. Harrison (1965), decision tables allow for the organization of complex rules in a structured and understandable way. Decision tables are composed of:

- conditions;
- rules;
- actions;
- expected results.

According to Dymova, Sevastjanov, and Kaczmarek (2016), decision tables improve:
logical consistency;
clarity of rules;
efficiency of the expert system.
Methodology
The methodology used in this study was based on the development of an expert system to support compressor maintenance, using knowledge acquisition techniques, production rules, decision tables, and computational implementation through Exsys Corvid.
Initially, a questionnaire was applied to experts in the field of industrial maintenance with the aim of collecting technical knowledge about failures, symptoms, causes, and maintenance procedures for compressors. The use of questionnaires as a knowledge acquisition technique in expert systems is widely referenced by Edward Feigenbaum in 1970, during the development of the first knowledge-based systems.
Subsequently, the data obtained were organized using decision tables, a technique proposed by Morton A. Harrison in 1965. The decision tables allowed for the logical structuring of combinations between conditions and actions, facilitating the representation of specialized knowledge related to compressor maintenance.

Table 1 : List of conditions and diagnostic

Condition(IF)	Diagnostic Action (THEN)
High discharge temperature	Check lubrication and filte
Low outlet pressure	Check leaks and valves
High oil consumption	Inspect seals and rings
Excessive vibration	Check alignment and bearings
Abnormal noise	Inspect mechanical components
High current	Check overload and voltage

Frequent starts	Check leaks and pressure switch
Heated bearings	Check lubrication and wear
Excess moisture	Check dryer and drains
Low energy efficiency	Check leaks and blockages
High Temperature and Excessive Vibration	Critical Failure
High Temperature	Overheating
Excessive	Vibration Unbalance

Source : Author

Table 2: Decision table

Condições/Acções	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	Else
High discharge temperature	1	0	0	0	0	0	0	0	0	0	0	0		0
Low outlet pressure	0	1	0	0	0	0	0	0	0	0	0	0		0
High oil consumption	0	0	1	0	0	0	0	0	0	0	0	0		0
Excessive vibration	0	0	0	1	0	0	0	0	0	0	0	0		0
Abnormal noise	0	0	0	0	1	0	0	0	0	0	0	0		0
High current	0	0	0	0	0	1	0	0	0	0	0	0		0
Frequent starts	0	0	0	0	0	0	1	0	0	0	0	0		0
Heated bearings	0	0	0	0	0	0	0	1	0	0	0	0		0
Excess moisture	0	0	0	0	0	0	0	0	1	0	0	0		0
Low energy efficiency	0	0	0	0	0	0	0	0	0	1	0	0		0
High Temperature and Excessive Vibration	0	0	0	0	0	0	0	0	0	0	1	0		0
High Temperature	0	0	0	0	0	0	0	0	0	0	0	1		0
Excessive	0	0	0	0	0	0	0	0	0	0	0	0	1	0
Check lubrication and filters	X													
Check leaks and valves		X												
Inspect seals and rings			X											
Check alignment and bearings				X										
Inspect mechanical components					X									
Check overload and voltage						X								
Check leaks and pressure switch							X							
Check lubrication and wear								X						
Check dryer and drains									X					
Check leaks and blockages										X				
Critical Failure											X			
Overheating												X		
Vibration Unbalance													X	
Check lubrication and filters														X

Source: author

Based on the information gathered, IF...THEN type production rules were developed, a technique also associated with the work of Edward Feigenbaum in 1970. These rules allowed the reasoning of industrial maintenance specialists to be represented in a logical and automated way.

Finally, the expert system was implemented using Exsys Corvid, developed by Exsys Inc. in 1984. Exsys Corvid enabled the creation of the knowledge base, implementation of decision rules, and construction of the inference engine responsible for the automatic diagnosis of compressor failures.

Expert System Implementation

Figure 1. Main screen for the expert system to support compressor maintenance
Source:author

Figure 2. Input data for the expert system to support compressor maintenance 1st screen.
Source:author

Figure 3. Input data for the expert system to support compressor maintenance 2nd screen.
Source:author

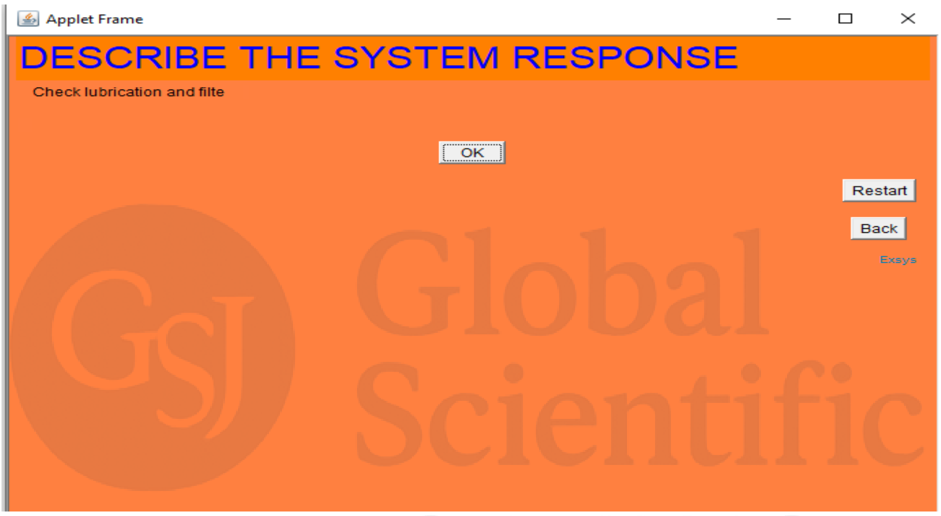

Figure 4. Output the expert system to support compressor maintenance results screen.
Source:author

The combination of these techniques has enabled the development of an efficient, organized expert system capable of supporting decision-making in the preventive and corrective maintenance of industrial compressors.

Discussion of Results

The comparative analysis between the proposed expert system and other international expert systems for compressor maintenance allowed us to identify important differences steps, which are:

Step 1: Classification Results

Suppose two evaluators assess whether a compressor is Acceptable or Not Acceptable.

Table 3 : Classification of results

Case	Evaluator A	Evaluator B
1	Acceptable	Acceptable

2	Acceptable	Acceptable
3	Acceptable	Acceptable
4	Acceptable	Not Acceptable
5	Not Acceptable	Not Acceptable
6	Not Acceptable	Not Acceptable
7	Not Acceptable	Acceptable
8	Not Acceptable	Not Acceptable

Step 2: Construct the Contingency Table

Table 4: contingency table

	B: Acceptable	**B: Not Acceptable**	**Total**
A: Acceptable	3	1	4
A: Not Acceptable	1	3	4
Total	4	4	8

Source: author

In interpretation, we have Agreement on **Acceptable**: 3 cases, Agreement on **Not Acceptable**: 3 cases and Disagreements: 2 cases.

Step 3: Calculate Observed Agreement (Po)

The observed agreement is:

$$P_o = \frac{3+3}{8} \quad P_o = \frac{6}{8} \quad P_o = 0.75$$

Thus, the evaluators agreed on **75%** of the compressor cases.

Step 4: Calculate Expected Agreement by Chance (Pe)

Probability both evaluators classify a compressor as **Acceptable**:

$$\left(\frac{4}{8}\right)\left(\frac{4}{8}\right) = 0.25$$

Probability both evaluators classify a compressor as **Not Acceptable**:

$$\left(\frac{4}{8}\right)\left(\frac{4}{8}\right) = 0.25$$

Therefore,

$$P_e = 0.25 + 0.25 = 0.50$$

Step 5: Calculate Cohen's Kappa

Use the formula:

$$\kappa = \frac{P_o - P_e}{1 - P_e}$$

Substituting the values:

$$\kappa = \frac{0.75 - 0.50}{1 - 0.50}$$

$$\kappa = \frac{0.25}{0.50}$$

K=0,50

Result:

K=0,50

Interpretation

According to the scale proposed by J. Richard Landis and Gary G. Koch (1977):

Table 5 : Interpretation of result

Kappa	Interpretation
< 0.00	Poor agreement
0.00–0.20	Slight agreement
0.21–0.40	Fair agreement
0.41–0.60	Moderate agreement
0.61–0.80	Substantial agreement
0.81–1.00	Almost perfect agreement

Source: author

Since

K=0,50

the agreement between the two evaluators is **moderate agreement beyond chance**.

Summary, Number of compressor cases: **8,** Observed agreement (Po): **75.0%**,Expected agreement (Pe): **50.0%**, Cohen's Kappa (K): **0.50** and interpretation: **Moderate agreement** (Landis & Koch, 1977).

The developed expert system successfully demonstrated the feasibility of applying Artificial Intelligence techniques based on production rules to support compressor maintenance activities. The knowledge acquired from maintenance specialists was effectively transformed into a structured knowledge base composed of decision tables and IF–THEN rules, enabling automated fault diagnosis and recommendation of corrective actions.

The implementation in Exsys Corvid allowed the creation of an inference mechanism capable of identifying maintenance scenarios from observable symptoms such as excessive vibration, high discharge temperature, abnormal noise, high oil consumption, and low outlet pressure. The decision table facilitated the organization and validation of maintenance knowledge, reducing inconsistencies and improving the transparency of the reasoning process.

To evaluate the system's performance, Cohen's Kappa coefficient was employed to compare system recommendations with expert judgments. The analysis produced an observed agreement of 75% and a Kappa coefficient of $K = 0.50$. According to the classification proposed by Landis and Koch (1977), this value represents a moderate agreement beyond chance.

The result indicates that the expert system is capable of reproducing a significant portion of the reasoning used by maintenance specialists. Although the agreement level is not classified as substantial or almost perfect, it demonstrates that the system can provide reliable support in fault diagnosis and maintenance decision-making. The discrepancies observed may be attributed to differences in expert interpretation, limitations in the number of diagnostic rules, and the complexity of real industrial maintenance scenarios.

Compared with modern predictive maintenance systems based on machine learning and sensor data analytics, the proposed system offers advantages such as simplicity, transparency, low implementation cost, and ease of maintenance. Furthermore, the explicit representation of knowledge through rules allows users to understand the reasoning process, an important characteristic in industrial environments where explainability is required.

The results suggest that the expert system can serve as a valuable decision-support tool, particularly in organizations where access to experienced maintenance specialists is limited.

Conclusion

This study presented the development and implementation of a Rule-Based Expert System for supporting industrial compressor maintenance. The proposed system was designed to assist maintenance technicians and mechanics in identifying equipment failures and recommending appropriate corrective actions through the use of expert knowledge represented as production rules and decision tables.

Knowledge acquisition was conducted through questionnaires administered to maintenance specialists, allowing practical expertise to be incorporated into the system's knowledge base. The implementation using Exsys Corvid enabled the development of an inference mechanism capable of performing automated diagnoses based on operational symptoms and maintenance indicators.

The validation process, carried out using Cohen's Kappa coefficient, produced a value of $K = 0.50$, indicating a moderate level of agreement between the system's recommendations and expert evaluations. This result demonstrates that the proposed expert system can effectively support maintenance activities and contribute to more consistent decision-making processes.

The research confirms that rule-based expert systems remain a viable and useful Artificial Intelligence approach for industrial maintenance applications due to their interpretability, simplicity, and ease of implementation. Future work may include expanding the knowledge base, incorporating fuzzy logic techniques to manage uncertainty, integrating real-time sensor data, and combining rule-based reasoning with machine learning methods to improve diagnostic accuracy and predictive maintenance capabilities.

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