African Journal of Advanced Pure and Applied Sciences (AJAPAS)
Online ISSN: 2957-644X
Volume 5, Issue 1, 2026
Page No: 357-370
Website: https://aaasjournals.com/index.php/ajapas/index
ISI 2025: 1.126 SJIFactor 2024: 6.752 معامل التأثير العربي: 1.62

Developing An Intelligent Maintenance DSS for Diagnosing Pump Faults Using Case-Based Reasoning Approach

Alhaam Mansour Aleisawi [1*], Saleh M. Amaitik [2]
[1] PhD Student, Department of Industrial and Production Engineering, School of Applied Sciences and Engineering, Libyan Academy, Tripoli, Libya
[2] Department of Industrial and Manufacturing Engineering, Misurata University, Misurata, Libya

تطوير نظام دعم القرار الذكي للصيانة لتشخيص أعطال المضخات باستخدام أسلوب الاستدلال القائم على الحالات

الهام منصور العيساوي المقصبي [1*]، صالح امعيتيق [2]
[1] طالب دكتوراه، قسم الهندسة الصناعية والإنتاجية، كلية العلوم التطبيقية والهندسة، الأكاديمية الليبية، طرابلس، ليبيا
[2] قسم الهندسة الصناعية والتصنيعية، جامعة مصراتة، مصراتة، ليبيا

*Corresponding author: elhammukasabi1974@gmail.com

Received: December 02, 2025	Accepted: February 20, 2026	Published: March 04, 2026

Abstract
This research paper presents a study on the development of an intelligent decision support system (DSS) for diagnosing pump faults using Case-Based Reasoning (CBR). The system was designed and tested using data from the Arabian Gulf Oil Company (AGOCO), focusing on centrifugal pumps.
The (CBR), is a relatively recent problem-solving technique that is attracting increasing attention and this technique provide a good solution in pump maintenance problems. Following the basic idea in CBR, experiences in solving previous similar pump maintenance problems are used to find the solutions for new problems. Good results are obtained from a wide range of experiments, and the results of the work are evaluated and some directions from this work are obtained.

Keywords: Case-Based Reasoning (CBR), Decision Support System, Fault Diagnosis, Predictive Maintenance, Centrifugal Pumps, Rotating Machinery, Similarity Retrieval, Oil Industry.

الملخص
تتناول هذه الورقة البحثية دراسة تطوير نظام دعم قرار ذكي لتشخيص أعطال المضخات باستخدام الاستدلال القائم على الحالات. صُمم النظام واختُبر باستخدام بيانات من شركة نفط الخليج العربي، مع التركيز على المضخات الطاردة المركزية. يُعدّ الاستدلال القائم على الحالات تقنية حديثة نسبياً لحل المشكلات، تحظى باهتمام متزايد، وتُقدم حلولاً فعّالة لمشاكل صيانة المضخات. وباتباع الفكرة الأساسية للاستدلال القائم على الحالات، استُخدمت الخبرات المكتسبة من حل مشكلات صيانة مضخات مماثلة سابقة لإيجاد حلول للمشكلات الجديدة. وقد حُققت نتائج جيدة من خلال مجموعة واسعة من التجارب، وجرى تقييم نتائج العمل واستخلاص بعض التوجيهات منه.

الكلمات المفتاحية: الاستدلال القائم على الحالات، نظام دعم القرار، تشخيص الأعطال، الصيانة التنبؤية، المضخات الطاردة المركزية، الآلات الدوارة، استرجاع التشابه، صناعة النفط.

1. General Framework and Methodology of the Study

1.1. Introduction:

Pump maintenance plays a critical role in ensuring reliable industrial operations, particularly in oil and gas facilities where pumps are essential components in fluid transportation systems. Failures in these systems may lead to production interruptions, safety risks, and significant economic losses.

Traditional expert systems for maintenance decision-making are typically based on predefined rules. However, these systems face major challenges in knowledge acquisition, knowledge representation, and system updating. Capturing expert knowledge in the form of rules is often difficult, especially when the knowledge is based on experience and practical observation.
Case-Based Reasoning (CBR) provides an alternative artificial intelligence approach that addresses these limitations. Instead of relying solely on predefined rules, CBR solves new problems by retrieving and adapting solutions from previously solved cases stored in a case database.
In maintenance applications, CBR is particularly useful because many faults reoccur with similar symptoms and causes. By storing historical maintenance experiences, engineers can quickly identify similar cases and apply proven solutions.
This research investigates the application of a CBR-based Decision Support System for diagnosing faults in centrifugal pumps used in oil production facilities. The system uses historical maintenance records collected from the Arabian Gulf Oil Company (AGOCO) to build a case library that supports fault diagnosis and maintenance decision-making.

1.2. Objectives of the Study:

The main objectives of this research are:

1. Exploring improvement opportunities in pump fault diagnosis through application of Artificial Intelligence technology in maintenance management.
2. Examining the application of Case-Based Reasoning methodology to a decision-support system for pump maintenance.

1.3. Literature Review:

Predictive maintenance and intelligent fault diagnosis for rotating machinery have received significant attention in recent decades due to their importance in improving reliability, reducing downtime, and lowering maintenance costs in industrial systems. Various knowledge-based and data-driven techniques have been developed to support maintenance decision-making, including expert systems, case-based reasoning (CBR), machine learning algorithms, and hybrid diagnostic models.
Early research focused primarily on expert systems that relied on domain knowledge to diagnose machinery faults. For example, M. Sarath Kumar and B. S. Prabhu (2000) developed an expert-system-based predictive maintenance approach for rotating machinery. Their study utilized detailed knowledge of vibration analysis and bearing condition monitoring to accurately predict machine health. The research highlighted the importance of integrating analytical methods with expert knowledge and user interaction in order to build effective diagnostic systems.
As maintenance strategies evolved toward condition-based maintenance (CBM), researchers began exploring techniques that could capture experiential knowledge from maintenance personnel. A case study conducted by the Knowledge Foundation (KK-Stiftelsen) (2002) demonstrated the development of a CBM system using sound analysis and case-based reasoning. The study showed that tacit knowledge from maintenance engineers could be incorporated as condition parameters within the diagnostic system. Similarly, Marcus Bengtsson, Erik Olsson, Peter Funk, and Mats Jackson (2004) further investigated CBM system design using sound-based monitoring for industrial robots. Their work demonstrated that maintenance personnel previously relied on manual auditory inspection to detect abnormal machine behavior. By integrating such experiential knowledge into a CBR framework, the researchers improved diagnostic reliability and decision-support capabilities.
Case-based reasoning has since become an important paradigm for industrial diagnosis because it allows systems to learn from previous maintenance experiences. Mark Devaney and Bill Cheetham (2005) applied CBR for gas turbine diagnostics and demonstrated that the approach could effectively identify root causes of equipment faults. Their study showed that the diagnostic accuracy of the CBR system was comparable to or better than traditional diagnostic methods. Similarly, Brigitte Chebel-Morello, Karim Haouchine, and Noureddine Zerhouni (2009) proposed a structured methodology for designing CBR-based industrial diagnostic systems. Their analysis of existing approaches revealed that, despite the widespread use of CBR in industrial diagnosis, there was no standardized methodology for developing such systems, indicating an important gap in the literature.
The flexibility of CBR has also been demonstrated in other diagnostic domains. For example, Mariam Baig (2008) applied CBR techniques to support stroke diagnosis in healthcare. Although the application domain differs from industrial maintenance, the study illustrated how new problems can be solved by retrieving and adapting solutions from similar historical cases. This capability makes CBR particularly useful in environments where expert knowledge is largely experiential.
In manufacturing maintenance applications, researchers have explored integrating CBR with analytical diagnostic methods. Y-T Tsai (2009) developed a CBR-based fault diagnosis system for injection molding machines by combining case-based reasoning with fault tree analysis and information flow analysis. The integration of structured fault analysis techniques enabled systematic identification of possible faults and symptoms, improving the diagnostic capability of the maintenance system.

Later studies expanded the application of CBR to rotating machinery diagnostics. H. Wang, J. Gao, and Z. Jiang (2012) proposed a fault diagnosis system based on CBR for rotating machinery components. Their research established a framework for representing and retrieving fault cases using historical maintenance data. The study emphasized that CBR is particularly effective for capturing experiential knowledge that is difficult to formalize into rule-based systems.
More recent research has incorporated advanced data-driven techniques to improve diagnostic performance. For instance, H. Zhang and Y. Bai (2017) developed a smart fault diagnosis system capable of automatically recognizing multiple rotor faults using neural networks and pattern recognition techniques. Their approach analyzed vibration spectrum images and shaft centerline orbits to detect abnormal machine conditions. Although not purely based on CBR, their work addressed the challenge of automated feature extraction from vibration data, which is also relevant to CBR-based diagnostic systems.
Handling uncertainty in fault diagnosis has also been investigated by several researchers. J. Xiong, C. Li, J. Cen, Q. Liang, and Y. Cai (2019) proposed an improved fault diagnosis approach based on evidence reasoning. Their method combined multiple sources of diagnostic evidence and introduced reliability calculations to address uncertainty in rotating machinery fault detection. Such approaches provide valuable insights for improving decision-making processes in knowledge-based diagnostic systems.
Another line of research has focused on similarity-based machine learning methods closely related to CBR. J. Lu, W. Qian, S. Li, and R. Cui (2021) proposed an enhanced K-Nearest Neighbor (KNN) algorithm for intelligent fault diagnosis of rotating machinery. Since KNN relies on retrieving the most similar historical instances, it shares conceptual similarities with CBR. Their approach incorporated dimensionality reduction and feature extraction through sparse filtering, addressing the problem of redundant or irrelevant features in diagnostic datasets.
Recent advancements have focused on improving the adaptability and learning capability of CBR systems. X. Xie, Z. Yang, L. Zhang, J. Wang, G. Zeng, X. Wang, and G. Chen (2023) proposed an improved CBR method that addresses a major limitation of traditional CBR systems—the inability to handle new fault patterns not present in the case library. Their approach introduced mechanisms for identifying unmatched cases and dynamically expanding the case base. Experimental validation using gear and bearing datasets demonstrated improved diagnostic performance.
More recently, hybrid approaches combining CBR with machine learning have been proposed to further enhance diagnostic accuracy. J. Li, Y. Guo, Y. Dou, J. Wang, B. Qiu, and X. Liu (2024) developed a hybrid diagnostic model that integrates case-based reasoning with ensemble learning techniques. In their approach, a Random Forest classifier optimized through Bayesian optimization was used to improve case retrieval and classification. The results showed that the hybrid system achieved superior diagnostic performance compared with standalone CBR or individual machine learning models.
The most recent developments emphasize the integration of CBR with structured fault analysis methods for predictive maintenance. V. Boishina and M. Sharkova (2025) proposed a diagnostic framework combining decision tree algorithms, fault tree analysis, and case-based reasoning to predict failures in industrial control devices. The system incorporated parameters such as material degradation, operating time under load, and contamination levels. Although the study focused primarily on control devices in power plants, the methodology can be extended to other industrial equipment such as pumps and turbines.
Despite the significant progress made in intelligent fault diagnosis, several challenges remain. Many diagnostic systems depend on predefined case libraries and may not effectively detect previously unseen faults. Additionally, feature extraction and data preprocessing remain complex tasks, particularly when dealing with vibration signals and multi-source condition monitoring data. Furthermore, relatively limited research has focused specifically on applying CBR-based diagnostic frameworks to pump systems operating in real industrial environments.
Therefore, there is a clear need for developing more adaptive and practical diagnostic frameworks that can utilize historical maintenance knowledge while also supporting the identification of new fault conditions. The present study aims to address this gap by developing a case-based reasoning system for rotating machinery fault diagnosis, with particular emphasis on pump maintenance. The proposed approach seeks to enhance maintenance decision-making by improving case representation, retrieval mechanisms, and the continuous expansion of the case library.

2. Development of a CBR System for Pump Maintenance

2.1. CBR Approach to Pump Maintenance:

A pump is a device used to move fluids, such as gases, liquids or slurries. A pump displaces a volume by physical or mechanical action. One common misconception about pumps is the thought that they create pressure. Pumps alone do not create pressure; they only displace fluid, causing a flow. Adding resistance to flow causes pressure. Pumps fall into five major groups: direct lift, displacement, velocity, buoyancy and gravity pumps.
A centrifugal pump is a rotodynamic pump that uses a rotating impeller to increase the pressure and flow rate of a fluid. Centrifugal pumps are the most common type of pump used to move liquids through a piping system. The fluid enters the pump impeller along or near to the rotating axis and is accelerated by the impeller, flowing radially

outward or axially into a diffuser chamber, from where it exits into the downstream piping system. Centrifugal pumps are typically used for large discharge through smaller heads.

The operating manual of any centrifugal pump often starts with a general statement, "Your centrifugal pump will give you completely trouble free and satisfactory service only on the condition that it is installed and operated with due care and is properly maintained."

There is other many conditions in which a pump, despite suffering no loss in flow or head, is considered to have failed and has to be pulled out of service as soon as possible. These include seal related problems (leakages, loss of flushing, cooling, quenching systems, etc), pump and motor bearings related problems (loss of lubrication, cooling, contamination of oil, abnormal noise, etc), leakages from pump casing, very high noise and vibration levels, or driver (motor or turbine) related problems.

The list of pump failure conditions mentioned above is neither exhaustive nor are the conditions mutually exclusive. Often the root causes of failure are the same but the symptoms are same.

When first symptoms of a problem appear can save the pumps from lasting failures by use the last solution, so the most important task in such situations is to find out and remember whether the pump has failed mechanically and has the same symptoms.

Effective troubleshooting requires an ability to observe changes in performance over time, and in the event of a failure, the capacity to thoroughly investigate the cause of the failure and take measures to prevent the problem from re-occurring and by good understanding and background.

A long time spend when the pumps are sent to the workshop, the maintenance people do not find the solution at the first time. Thus the decision to maintenance / repair should be made after a detailed analysis of the symptoms and root causes of the pump failure.

2.2. CBR System Framework:

The core of CBR is a case base which includes all the previous experiences that can give us information we can use to deal with new problems. Then, through the similarity concept, the most similar experiences are retrieved. However, similarity is not a simple or uniform concept. Similarity is a subjective term that depends on what one's goals are.

In our approach, the case base represents the user profile and consists of a set of previous experiences (cases); that is, items explicitly and/or totally assessed by the user. Each case contains the item description and the interest attributes describing the interests of the user concerning the item. These latter attributes can be explicitly given by the user or absolutely captured by the system.

First, the system collects data about the pump maintenance of an organization by the job card from mechanical section fault and repairs shown in table below:

If the memory provides a relevant case at this point, the system focuses on the analysis of assets of the previous cases to see whether anything can be adopted from it.

2.3. Data Collection and Source:

The data collected were taken from **Arabian Gulf Oil Company at Al Sarir oilfield** especially from mechanical section fault and repair, the study equipments are three types of pumps.

Table (1): Framework of Parameter

<table>
<tr><th colspan="3">Input data</th></tr>
<tr><th>C)Operation condition</th><th>B) Motor Data</th><th>A) Pump data</th></tr>
<tr><td>Liquid:
Pump temp.:
Sp. Gravity:
Viscosity:</td><td>Manufacturer:
Type:
Serial No.:
Power:
Speed:
Phase:
Frequency:
Insulation class:
Ex-protection:
Voltage:
Temp.:</td><td rowspan="3">Manufacturer:
Pump type:
Pump function:
Design no:
Model:
Serial no:
Capacity:
No of stage:
Speed:
Inb . brg .no :
Outb .brg .no:
Discharge pressure:
Suction pressure:
Hydro .test:
Year built:
Comm. date:
Pump lubricating:
Suction:
Discharge:</td></tr>
<tr><th colspan="2">D)Fault type</th></tr>
<tr><td colspan="2">Fault type:
Fault description:</td></tr>
</table>

If a case of a past pump maintenance is recalled, the system attempts to find out whether it is possible for the current case. Then the system produces initial results from the recall and adaptation process.

2.4. Case Representation:

A case-based reasoning is heavily dependent on the representation and content of its collection of cases.

In our approach, a case represents the user's experience concerning a certain item. Cases are dividing into two parts: the first, Input data (Pump data, Motor data, Operation condition and Fault type) it is the definition of the problem in CBR terminology, and the second, Output data (Fault found duo to, spears used, total cost of spares, number of hours, number of craftsmen, and other action) the solution to the problem in CBR terminology.

- We use the Flat feature-value list method, this choice of representation is

Dependent on requirements of domain and task and structure of already available case data.

Flat Memory, Serial Search. Cases are stored sequentially in a simple list, array, or file. No explicit indexing structure is created, and searching is done sequentially, case by case, until the entire case library is searched. If the matching heuristic is effective, the best-matching case will always be retrieved. Adding new cases to a case library is also simple and straightforward (e.g., the case is added as the last element of a list).

Thus, given a set of items

$P = \{p1, p2, \ldots, ps\}$,

each item is characterized by a set of objective attributes,

$pi = \{at_{i1}, at_{i2}, \ldots, at_{in}\}$

and at is the set of all possible attributes. In general, objective attributes do not tend to be very complex, consisting largely of descriptive adjectives, nouns or values. Each user has a different degree of interest in any given items and interest can be expressed by the user (explicit attributes) or captured automatically by the system as a result of user interactivity (implicit attributes). Explicit interest provides more confidence in the recommendation process.

However, this is not always available. Implicit interest is useful when deciding upon interesting items for the user. In our model we distinguish both kinds of user interactions: explicit from implicit and, therefore, a hybrid approach. We name the set of explicit interest as: $Int^e = \{int^e1, int^e2, \ldots, int^em\}$

and the set of implicit interest as: $Int^i = \{int^i1, int^i2, \ldots, int^il\}$

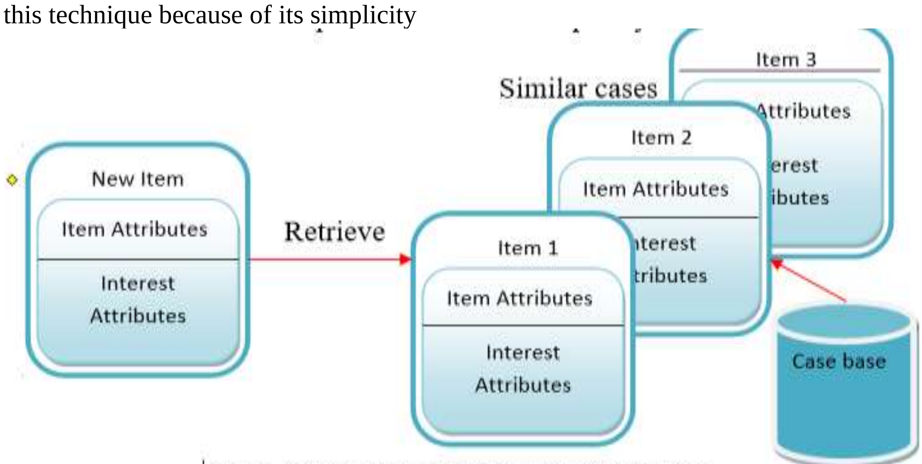
Both int^ej and int^ij are defined in [0, 1].

Each user has experiences in several items. An experience keeps information about the objective attributes of a given item as well as subjective information concerning the interest of the user in that item. Thus,

$E_i =< p_i, Int^e_i , Int^i_i , \delta_i >$,Where $pi \subset P$ is the set of objective attributes of the item, $Int^e_i \subset Int^e$ is the set of explicit interest, $Int^i_i \subset Int_i$ is the set of implicit interest, and δi is a temporal parameter in [0-1] that indicates the relevance of the experience. This parameter is called the drift attribute. Initially δ is set to 1, and is updated according to the evolution of the user profile.

Finally, if a case represents the experience of the user in a given item, the complete case base constitutes the user profile representation which models the user. So, the recommender system keeps a case base for each user representing their profile. In order to start recommending to the user, the system needs to fill in the user profile; that is, the set of initial experiences in the case base. The initial experiences are generated through the use of the training set technique. That is, users are driven to a set of items and they have to fill in information about their interest in these items. The item set consists of a collection of selected items. For each item in the set, the system asks the user about the explicit interest and also gathers information related to implicit interests.

The selection of a suitable initial item set is indeed very difficult. Users are often asked about items that they do not know and they have to invent an evaluation taking into account their attributes. Despite such limitation, we have chosen this technique because of its simplicity



Item Attributes and Interest Attributes

2.5. Case Indexing:

Case indexing refers to the task of labels to the cases that are entered into the case library to facilitate the case retrieval process. Features related to the Pump data, Motor Data, Operation condition and Fault type as shown in table below are considered in the case indexing. Another issue of case indexing is to identify the critical features in order to facilitate effective the case retrieval.

There are various techniques for identifying the most critical feature and determining the importance weighting of individual features, this represents a decision maker's initial overall preference structure.

The initial importance weightings can be obtained by the decision maker and experience.

Thirty seven features of a case with their corresponding initial weightings are shown in table below:

Table (2): A list of input features.

Input data		Input features	Initial importance weights
Pump data	X1	Manufacturer	1
	X2	Pump Type	3
	X3	Pump Function	3
	X4	Design Number	3
	X5	Model	2
	X6	Serial Number	3
	X7	Capacity	1
	X8	Number of Stages	2
	X9	Maximum Head	1
	X10	Pump Speed	1
	X11	Input Bearing Number	1
	X12	Output Bearing Number	1
	X13	Discharge Pressure	1
	X14	Suction Pressure	1
	X15	Hydro Test	1
	X16	Year Built	1
	X17	Commercial Date	1
	X18	Pump Lubrication	1
	X19	Suction	1
	X20	Discharge	1
Motor Data	X21	Motor Manufacturer	1
	X22	Motor Type	1
	X23	Motor Serial Number	1
	X24	Power of Motor	1
	X25	Motor Speed	1
	X26	Motor Phases	1
	X27	Motor Frequencey	1
	X28	Insulation Class	1
	X29	External Protection	1
	X30	Voltage	1
	X31	Temperature	1
Operation condition	X32	Liquid Type	2
	X33	Pump Temperature	1
	X34	Specific Gravity	1
	X35	Viscosity	1
Fault type	X36	Fault Type	3
	X37	Fault Description	3

2.6. Case Library Design

Case library stores the previously successful cases in a predefined structure and organization. A case comprises a description of problem, solution and outcome. In the CBR, the features (input data) as shown in table below are used to describe a problem case. When a new problem is occur, the data and/or information of these features for a new problem case are input to the CBR. The output from the CBR contains 6 parameters settings as shown in the following table:

Table (3): Output Data

Output features
Fault found duo to: (P. M. Initial-Break down- Repair-Others). Spears used: Total cost of spares: Number of hours: Number of craftsmen: Other action:

The outcome of a case could be about the fault found duo to, spears used, total cost of spares, number of hours, number of craftsmen, and other action. Therefore, any case in the case library can be represented as:

$$\text{Case} \quad \{ \ \mathbf{Pi, Si, Oi} \ \}$$

Where **Pi** is a set of problem descriptions of the case i, **Si** is a solution set of the case i, and **Oi** is a set of outcome of the case i.

The cases are represented in attribute - value pairs in which each case stored in the case library is described by a set of features and their corresponding values or information.

The attribute - value pairs were chosen for representing cases because they are similar to the input and output data parameters setting.

Its simplicity and easy understanding make it adequate in the development of a prototype system in this research. Another consideration of the case library design is case organization. The case library can be organized in various forms such as a linear list of cases, a hierarchy of classes of cases, a semantic network-like structure or a combination of all of these forms. In the CBR system, the case library is organized as the combination of a linear list.

2.7. Case Retrieval:

Retrieval Knowledge includes features used to index cases and relative importance of features used for similarity, and the first step in the CBR process is the retrieval of similar prior events. In this step the case library is queried for prior events that are most similar to the current incident to be diagnosed. A custom nearest-neighbor technique is used to retrieve some number of cases that form the input of the next stage in reasoning.

2.7.1. Similarity assessment:

The most important step in the retrieval phase of CBR is to define the degree of similarity between cases. The success of CBR systems depends primarily on the capacity of the system to exhibit how similar two cases are. With an efficient similarity measure, given a case we can obtain an ordered list of similar cases. Taking advantage of this concept, when a user likes an item, the recommender system can recommend to him/her a list of similar items that the user should like.

The degree of similarity between two items is computed by a global similarity function. The global similarity is calculated from a weighted ponderation of the various attribute similarities. For the numeric attributes, linear and exponential functions have been. For labeled attributes, we have generated similarity tables, where the similarities among the different attribute labels are predetermined. Once the similarities between the new case and the cases in the case base are calculated, a set of best matches is chosen. In our implementation, we select the *x* best cases provided which exceed a minimum selection threshold.

2.7.2 Nearest-neighbor retrieval:

Nearest-neighbor retrieval technique is to measure similarity between source case and case which we are searching. If case is not matched with CBR library.

Then, CBR system will return nearest match. Nearest match can be represented in following equation.

$$\frac{\sum_{i=1}^{n} w_i \times sim\left(f_i^I, f_i^R\right)}{\sum_{i=1}^{n} w_i}$$

To calculate the Wi in this input and output data which include two types of value (textual and numerical) we need this two equation :

- **Textual data:** $\text{wi} = \begin{cases} 1, & w = w\,i \\ 0, & otherwaise \end{cases}$
- **Numerical data:** In minimum value $\text{Wi} = \frac{\text{Win} - \text{Wmin}}{\text{Wcase} - \text{Wmin}}$, Wmin≤Win≤Wcase

  In maximum value $\text{Wi} = \frac{\text{Wmax} - \text{Win}}{\text{Wmax} - \text{Wcase}}$, Wcase≤ Win≤Wma

Where:
Wi: is the importance weighting of each parameter.
Win: is the importance weighting of input parameter.
Wmax: is the importance weighting of maximum value in this parameter.
Wmin: is the importance weighting of minimum value in this parameter.
Wcase: is the importance weighting of case parameter.

2.8. Case Reuse:

The reuse phase consists of adapting the old solutions of the retrieved cases to the new problem based on the differences among them. Once the system has retrieved a set of previous items (the most similar ones), the system knows the user's interest in similar items through the interest attributes (solution in CBR terminology). Assuming that the user's interest in a new item is similar to the user's interest in similar items, in the reuse phase, the recommender system calculates an interest confidence value for the new item. This value is used to decide whether to recommend the new item to the user.

The reuse of the retrieved case solution in the context of the new case focuses on two aspects: (a) the differences among the past and the current case and (b) what part of a retrieved case can be transferred to the new case.

3.7.1 Copy

In simple classification tasks the differences are abstracted away (they are considered non relevant while similarities are relevant) and the solution class of the retrieved case is transferred to the new case as its solution class. This is a trivial type of reuse. However, other systems have to take into account differences in (a) and thus the reused part (b) cannot be directly transferred to the new case but requires an *adaptation* process that takes into account those differences.

3.7.2 Adaptation

Adaptation proposed two types of solution:

- Null adaptation - copy retrieved solution used by CBR systems
- Manual or interactive adaptation user adapts the retrieved solution

The system described does not include a procedure for adaptation: this is carried out by the operator or user. This does not mean that the adaptation should not be studied carefully. When the system is implemented according to the principle that is presented above, retrieval will carry out the cases, because usually, it selects several forms by allowing final selection make by operator.

However, attaching to the principle of retrieval guided by the adaptation it is required ideally, that the retrieval decide a source case over another, if the first case demands less *adaptation effort* to solve the target problem than the second (Adaptation effort concept is quite practical to give an intuition, but would value to be better defined within general framework of CBR. To specify this intuition within the framework of the considered CBR system in this paper it will be considered that this effort is "the cognitive effort" of operator to solve the target problem knowing that it arranges the source case.

In this case, on which parameter of retrieval procedure should we act in order that it would be guided by adaptation? The question is acceptable: in the presentation made above there is several parameters. On response, the problems (especially) must be represented in an appropriate language to be directed by computer and it must be translated by an expression of this language.

However, this language is necessarily poorer than the natural language; this translation comes with loss of the information. The parameter on which we act to take into account the adaptation at the time of the retrieval is the choice of this language.

We can illustrate this idea by following example. We can suppose that two electric problems (or two mechanic problems) are necessarily closer between them-in adaptation effort sense –compared with two problems of which one is electric and other mechanic. This proposes that the problem representation language must be able to differentiate the electric problems from the mechanical problems. Generally, the problems of choosing a problems representation language in order to do a retrieval guided by adaptation are problems of knowledge acquisition which is in progress.

This acquisition is done on the basis of the existing forms and discussion with the operators who setup these forms.

2.8. Case Revision:

When a case solution generated by the reuse phase is not correct, an opportunity for learning from failure arises. This phase is called case revision and consists of two tasks: (1) evaluate the case solution generated by reuse. If successful, learning from the success (case retainment, see next section), (2) otherwise repair the case solution using domain-specific knowledge.

2.8.1 Evaluate solution:

The evaluation task takes the result from applying the solution in the real environment (asking a teacher or performing the task in the real world). This is usually a step outside the CBR system, since it - at least for a system in normal operation - involves the application of a suggested solution to the real problem. The results from applying the solution may take some time to appear, depending on the type of application. In a medical decision support system, the success or failure of a treatment may take from a few hours up to several months. The case may still be learned, and be available in the case base in the intermediate period, but it has to be marked as a non-evaluated case. A solution may also be applied to a simulation program that is able to generate a correct solution. This is used in CHEF, where a solution (i.e. a cooking recipe) is applied to an internal model assumed to be strong enough to give the necessary feedback for solution repair.

2.8.2. Repair fault:

Case repair involves identifying the errors of the current solution and retrieving or generating explanations for them. The best example is the CHEF system, where causal knowledge is used to generate an explanation of why certain goals of the solution plan were not achieved. CHEF learns the general situations that will cause the failures using an explanation-based learning technique. This is included into a failure memory that is used in the reuse phase to predict possible shortcomings of plans. This form of learning moves detection of errors in a post hoc fashion to the elaboration plan phase where errors can be predicted, handled and avoided. A second task of the revision phase is the solution repair task. This task uses the failure explanations to modify the solution in such a way that failures do not occur. For instance, the failed plan in the CHEF system is modified by a repair module that adds steps to the plan that will assure that the causes of the errors will not occur. The repair module possesses general causal knowledge and domain knowledge about how to disable or compensate causes of errors in the domain. The revised plan can then be retained directly (if the revision phase assures its correctness) or it can be evaluated and repaired again.

2.9. Case Retain:

The retention process is the enhancing of the case base with the revised case thus allowing the system to learn and we need to know what can be learned

- New experience to be retained as new case

Representing the new case: Contents of new case and indexing of new case

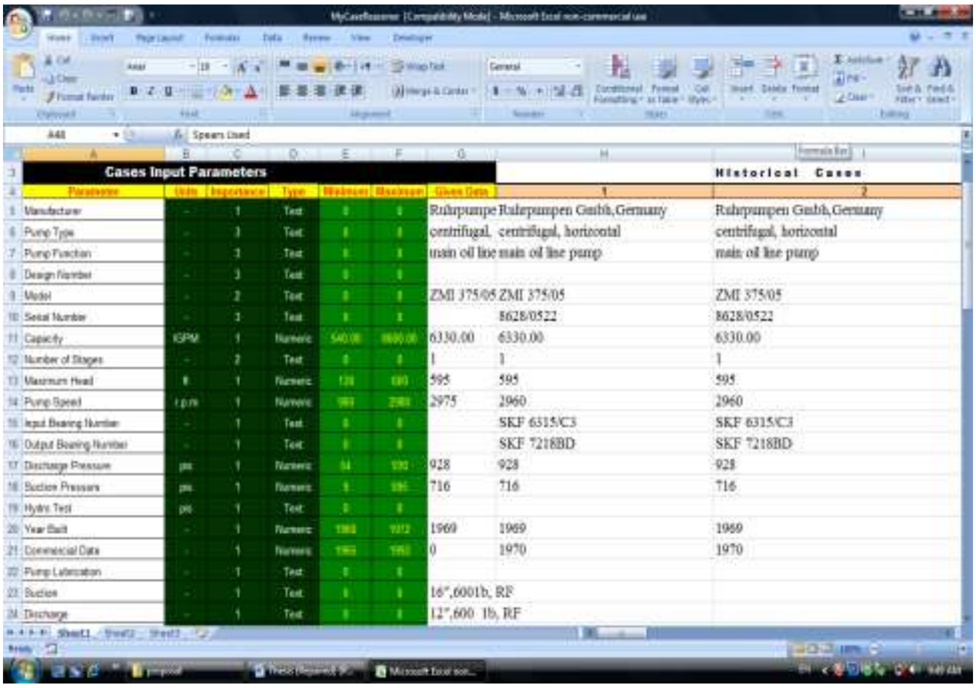
The learning occurs as a by-product of the problem-solving process and represents learning by experience. Successful new solutions are added to the case memory to facilitate similar problems in the future and failures can be added to avoid repeating the same mistakes.

Increasing the number of example situations in the case base means that the system covers more of the domain and will work better. However, increasing the size of the case-base indiscriminately leads to a problem known as the *utility problem*.

After a certain point, adding more cases to a case-base will result in a reduction in the efficiency of the case-base. This comes from the fact that retrieval time will increase but the adaptation savings tend to reduce as more cases are added.

2.10. System Implementation and Validation:

The CBR system has been implemented using visual basic programming language in Microsoft Excel. Users are first required to input the data and information about the pump data, motor data, operation condition and fault type information. The CBR system will then perform the case retrieval and case adaptation to the solution of new problem as showing below:



We compare the solution quality of three cases with solution of CBR techniques and good quality solutions obtained; we also evaluate how these techniques perform the pump maintenance problem and there are no large different between the solutions and a set of the most similar cases is selected to help the decision maker.

It is clear from an examination of the workings of the CBR techniques that they can be used to produce solutions for problems.

3. Results and discussions

3.1. Results:

The case-based reasoning approach was used to create a case-base for the pump maintenance. Over eleven years (from 1995 until now) of historical data from the AGOCO company maintenance system was used in the case-based stage.

The case establishment stage resulted in a case-base from the pump maintenance over 92 cases [17], then we inlet the new case and run the program to obtained the solution of problem by given us the percentage to the case are similar to the new case which help us to make decision support.

New problem can be solved by retrieving similar problems, retrieved solutions and then similar problems have similar solutions.

<table>
<tr><th colspan="3">Input data</th></tr>
<tr><th>C)Operation condition</th><th>B)Motor Data</th><th>A) Pump data</th></tr>
<tr><td>Liquid: crude oil.
Pump temp.: 130° f.
Sp. Gravity:
Viscosity: 48.8 SSU.</td><td>Manufacturer: Parsons, Peebles, Scotland.
Type: MT-7105J.
Serial No.:
Power: 1270 HP.
Speed: 2960 r.p.m.
Phase: 3.
Frequency:50 HZ.
Insulation class:{F}
Ex-protection: Approved for division 2 areas.
Voltage: 3300V.
Temp.:</td><td rowspan="3">Manufacturer: Ruhrpumpen Gmbh, Germany.
Pump type: centrifugal,horizontal.
Pump function: main oil line pump.
Design no:
Model: ZMI 375/05.
Serial no:
Capacity:7300 IGPM
No of stage: 1.
Max. Head: 500 ft.
Speed: 2960 r.p.m.
Inb . brg .no :
Outb .br .no: Discharge pressure: 782 pisg
Suction pressure: 182 pisg
Hydro .test:
Year built: 1968.
Comm. date:
Pump lubricating:
Suction: 16″,6001b, RF.
Discharge: 12″ 600 1b, RF.</td></tr>
<tr><th colspan="2">D)Fault type</th></tr>
<tr><td colspan="2">Fault type: mechanical.
Fault description: N.D.E mechanical seal leaking.</td></tr>
</table>

Case study number one

For discussion of the results we need new problem (new case study number one and tow) which is a case without a solution part to examine the results; this case study number one is appearance in table below:

After that, compare a new problem to each case and select the most three similar ones.

The similarity is most important concept in CBR, so to find the similarity of cases we have to know the similarity percentage by weighted Average of first three cases that are most similar, that appears in running of the program and then we can get the results as mentioned above (table 4 similarities of cases).Similarities of cases (case study number one)

Retrieve Case

Parameter	Units	Given Data	86	83	78	79	80	82	87	84
Manufacturer	-	Ruhrpumpen G	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Pump Type	-	centrifugal, hori	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Pump Function	-	main oil line pu	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Design Number	-		1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Model	-	ZMI 375/05	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Serial Number	-		1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Capacity	IGPM	7300.00	1.00	1.00	0.85	0.85	0.85	1.00	1.00	1.00
Number of Stages	-	1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Maximum Head	ft	500	1.00	1.00	0.89	0.89	0.89	1.00	1.00	1.00
Pump Speed	r.p.m	2960	1.00	1.00	0.99	0.99	0.99	1.00	1.00	1.00
Input Bearing Number	-		1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Output Bearing Number	-		1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Discharge Pressure	pis	782	1.00	1.00	0.20	0.20	0.20	1.00	1.00	1.00
Suction Pressure	pis	182	1.00	1.00	0.20	0.20	0.20	1.00	1.00	1.00
Hydro Test	pis		1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Year Built	-	1968	1.00	0.00	0.89	0.89	0.89	1.00	1.00	0.00
Commercial Date	-	0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pump Lubrication	-		1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Suction	-	16",6001b, RF	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Discharge	-	12",600 1b, RF	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Motor Manufacturer	-	Parsons, Peeble	1.00	1.00	0.00	0.00	0.00	1.00	1.00	1.00
Motor Type	-	MT-7105J	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Motor Serial Number	-		1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Power of Motor	HP	1270	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Motor Speed	r.p.m	2960	1.00	1.00	0.99	0.99	0.99	1.00	1.00	1.00
Motor Phases	-	3	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Motor Frequencey	HZ	50	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Insulation Class	-	{F}	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
External Protection	-	Approved for di	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Voltage	V	3300	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Temperature	° f	0	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Liquid Type	-	crud oil	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Pump Temperature	° f	130	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Specific Gravity	kg/dm3	0.84	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Viscosity	SSU	48.8	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Fault Type	-	mechanical	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Fault Description		N.D.E mechanic	1.00	1.00	1.00	1.00	1.00	0.00	0.00	0.00
Similarty by weighted Average			0.96	0.94	0.90	0.90	0.90	0.90	0.90	0.88

Similarity for each parameter which is depends on parameter values are computed as total percentage, The first three values of previously cases can be seen in Table 4.2, as we see the first three values of similarity by weighted average are: 0.96, 0.94 and 0.9 these three values are against to three cases number: 86, 83 and 78 respectively. Three cases which are similar to a given case are considered to be the most similar to the new problem and are retrieved from the case base. The structures of study obtained **three cases**.

The first one (case number 86) has the same solution put there are some different.
The results are a mixture of cases with small difference in few parameters as the following:

The **first** result that has the high percentage of similarity (0.96) there are few difference in two cases in their solutions, the changed is too small appearance in:

- Total cost of spares this difference because the cost of spares is changed in every year.
- Number of hours is depending on the worker (if they have experience or they are slow or number of them and so on) and depending on the pump condition.
- Other action some workers do not write the all action taking like this alignment, changed oil, adjusted clearance ext.

The **second** result is having the percentage of similarity (0.94) there are few different in two cases in their solution; the changed is appearance in:

- Spears part used are same but the thrust bearing is used in here it is depended on some damage in thrust during repair.
- And the different in total cost of spares, number of hours, and other action are same reason explained in above.

The **third** result is having the percentage of similarity (0.90) there are few different in two cases in their solution; the changed is appearance in:

- Spears part used are same but the shaft sleeve is not used in here it is depend on; some workers use the spears from the workshop or from the old spears and they do not writ it because the cost of it not computed in the repair.
- And the different in total cost of spares, number of hours, and other action are same reason explained in above.
- To confirm the results, we need another case (new case study number tow) which is a case without a solution part to assess the results; this case study number tow.
  Similarity percentage by weighted Average of first three cases that are most similar, that appears in running of the program and then we can get the results as we see.

3.2. discussions:

<u>From all the previous we see that:</u> Possible results of retrieval cases could be:

· No cases retrieved – meaning no match found
· All cases retrieved are of the same category, or
. There are some different in solution– meaning we need to adapt

So, the quality of data and high quantity of data are the essential in case-based reasoning for any research.
Experiments showed that the CBR-based DSS successfully diagnosed pump faults by retrieving similar cases and adapting solutions. Case studies demonstrated high accuracy in fault identification and reduced maintenance time. The findings confirm that CBR is a robust technique for pump fault diagnosis. Compared to rule-based systems, CBR reduces complexity of knowledge acquisition and allows continuous learning. The DSS provides practical benefits for maintenance engineers, enabling faster troubleshooting and minimizing downtime.

4. The Conclusion and recommendations:

4.1. Conclusion:

The study confirms that CBR is a suitable technique for pump fault diagnosis. The DSS improves maintenance efficiency, reduces downtime, and enhances learning by continuously updating the case base. Future work may integrate predictive analytics and IoT-based monitoring for real-time fault detection.
a discussion of results that were derived from this study. It also outlines the contributions that were made by the application of this computational technique to the knowledge base.
And investigates the CBR for solving pump maintenance problems, the overall objective is to study how CBR can help to solve this type of maintenance problem by reusing previous knowledge collected and stored in a case base and making it available, adapted and applied to new situations.
The CBR system presented a simple approach towards reasoning in this domain by providing a flexible case representation, an efficient case base organization and an effective retrieval algorithm.
CBR will help solving the pump maintenance problem by provide a flexible system, it can be applied to any decision support system where information can be represented as attribute-value pairs, and where problems are solved by iteratively accessing and using previously resulting information.We have established through knowledge acquisition and knowledge representation that applying CBR is possible and successful management system for solve pump maintenance problems.

4.2. Recommendations:

It is recommended to adopt CBR system for the maintenance of pump at AL Sareir oilfield; this will improve the maintenance performance as we see in the results.

4.3. Future work:

Similar research can be done for another type of equipment (air compressor, turbine, motor, and ext.) by use the same technique (CBR) in maintenance.

Some methods used to obtain the importance weight such as direct assignment technique, eigenvector method, entropy method and minimal information method these methods give us exact evaluation and it can provide a more flexible way of acquiring and representing favorite information.

Compliance with ethical standards

Disclosure of conflict of interest

The author(s) declare that they have no conflict of interest.

References:

1. Aamodt, A., & Plaza, E. (1994). Case-based reasoning: Foundational issues, methodological variations, and system approaches. AI Communications, 7(1), 39-59.
2. Bengtsson, M., Olsson, E., Funk, P., & Jackson, M. (2004, May 2-5). Technical design of condition based maintenance system: A case study using sound analysis and case-based reasoning [Conference presentation]. Maintenance and Reliability Conference (8th Congress), University of Tennessee, Knoxville, TN, United States.
3. Boishina, V., & Sharkova, M. (2025). Control devices faults prediction using decision tree and case-base reasoning. Union of Automation and Informatics "John Atanasov", Bulgaria.
4. Chebel-Morello, B., Haouchine, K., & Zerhouni, N. (2009). A methodology to conceive a case based system of industrial diagnosis.
5. Devaney, M., & Cheetham, B. (2005). Case-based reasoning for gas turbine diagnostics. In 18th International FLAIRS Conference (FLAIRS-05). American Association for Artificial Intelligence.
6. Fouzia, A., & Mokhtar, S. (2009). Knowledge management for fault diagnosis of gas turbines using case based reasoning (Vol. 10).
7. [Ian, W., & Farhi, M. (1994). Case-based reasoning: A review (Vol. 9).
8. KK-Stiftelsen. (2002). Technical design of condition based maintenance system [Technical report].
9. Larry, B., & Angel, C. (2003). Know and understand centrifugal pumps.
10. Li, J., Guo, Y., Dou, Y., Wang, J., Qiu, B., & Liu, X. (2024). An approach to bearing fault diagnosis based on ensemble learning and case-based reasoning. Journal of Physics: Conference Series, 2787(1), 012020.
11. Lu, J., Qian, W., Li, S., & Cui, R. (2021). Enhanced K-nearest neighbor for intelligent fault diagnosis of rotating machinery. Applied Sciences, 11(3), 919.
12. Mariam, B. (2008). Case-based reasoning – An effective paradigm for providing diagnostic support for stroke patients.
13. Michael, M., & Agnar, A. (2006). Case-based reasoning foundations. The Knowledge Engineering Review, 20(3), 203–207.
14. Rong Qu.; case-based reasoning for course timetabling problems, (2002).
15. Sarath Kumar, M., & Prabhu, B. S. (2000). Rotating machinery predictive maintenance through expert system. International Journal of Rotating Machinery, 6(5), 363-373.
16. Danny K.Y. Sin & James N.K. Liu; Optimization Approach using Case Based Reasoning and Evolution Strategy, (2001).
17. Sottile, J., Jr., & Kohler, J. L. (1989). Techniques for improved predictive maintenance testing of industrial power systems. IEEE Transactions on Industry Applications, 25(6), 992-999.
18. Tsai, Y.-T. (2009). Applying a case-based reasoning method for fault diagnosis during maintenance.
19. Wang, H., Gao, J., Jiang, Z., et al. (2012). Research of rotating machinery fault diagnosis system based on case-based reasoning. Science Technology and Engineering.
20. Xie, X., Yang, Z., Zhang, L., Wang, J., Zeng, G., Wang, X., & Chen, G. (2023). Fault diagnosis method for rotating machinery based on improved CBR. Journal of Physics: Conference Series, 2528(1), 012014.
21. Xiong, J., Li, C., Cen, J., Liang, Q., & Cai, Y. (2019). Fault diagnosis method based on improved evidence reasoning. Mathematical Problems in Engineering, 2019, Article 7491605.
22. Zhang, H., & Bai, Y. (2017). A smart diagnosis system based on automatic recognition of multiple rotor faults. Advances in Mechanical Engineering, 9(9).

Websites
1. AI-CBR. (n.d.). AI-CBR: AI and case-based reasoning. Retrieved [Access Date if known], from http://www.ai-cbr.org.
2. Arabian Gulf Oil Company AGOCO. Retrieved from http://www.agocooil.com.
3. Wikipedia. (n.d.). Libya. Retrieved from http://en.wikipedia.org/wiki/Libya.
4. Wikipedia. (n.d.). Pump. Retrieved from http://en.wikipedia.org/wiki/pump.

