World Journal of Advanced Engineering Technology and Sciences
eISSN: 2582-8266
Cross Ref DOI: 10.30574/wjaets
Journal homepage: https://wjaets.com/

(Research Article)

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Process equipment design using case-based reasoning

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World Journal of Advanced Engineering Technology and Sciences, 2022, 06(01), 053–064

Publication history: Received on 02 May 2022; revised on 09 June 2022; accepted on 11 June 2022

Article DOI: https://doi.org/10.30574/wjaets.2022.6.1.0064

Abstract

The need for proper design of process equipment cannot be over emphasized in view of the vast human and technical involvement in every design activity. There is therefore the need to accomplish this design accurately and as fast as possible. The conventional approach adopted in the design process is to use mathematical models to obtain relevant design parameters. Accurate computation of the design parameters of new equipment is one of the main concerns of design engineers implementing different projects. Since some of features of an equipment cannot be expressed quantitatively and there are many qualitative features in data of the available process equipment. So, a method should be applied to use these data to estimate the desired and ideal output of design engineer. The case-based reasoning (CBR) method covers the qualitative data with regard to its nature. Using CBR method which is created based on the viewpoint of using previously solved problems in order to solve new similar problem save time and therefore speed of design is increased which is very important when considering the time required to estimate output which are design parameter in this case study. This research effort aims to use a Case-Based Reasoning (CBR) approach for process equipment design and attempts to investigate its advantages over traditional design approach.

Keywords: Case Based Reasoning; Gas Cyclone; Cyclone Efficiency; Pressure Drop; K-Nearest Neighbor

1. Introduction

In the domain of process equipment design, there are many problems that are difficult to solve purely by traditional mathematical modelling approaches due to many uncertainties as well as numerous simplifications and assumptions. This design is usually based on the application of mathematical models derived to simulate the operation of such equipment and in some instances are subjected to subjective judgments of the design engineer. Designs have to handle a dynamic context with a lot of unexpected events. The more experienced design engineers are, the more likely it is that they can make the right decisions within critical situations. They can draw on experiences collected within similar situations in the past. Although there could be vast databases for systemizing, analysing and transforming data, such data can still be improved to extract more information and knowledge. Also, some equipment data are measured indirectly and therefore can be inconsistent. Most of the data are used for design applications without creating reasoning for the extraction and expansion of the body of knowledge. There are numerous and valuable knowledge hidden behind the data. Human reasoning is therefore required to translate data to information and information to the knowledge. Moreover, the valuable experience gained through the cases is generally not stored or systemized in order to reuse in the future situations. Knowledge is also lost when experienced people leave the companies. The goal here is to find a method to re-use experience from past cases to solve new complex process equipment design problems where the traditional design techniques are not capable of solving those challenges alone. This method should extract stored and hidden knowledge from the cases and incorporate it with the existing knowledge for added value.

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Therefore, in addition to the existing computing tools or databases, a knowledge-based approach is needed in order to be able to reuse the experience and lessons learned from real cases. In this research work, we introduce an approach where we collect knowledge from design engineers and transfer that knowledge into a Case-Based Reasoning system. Thus, experiences describing exceptional situations are stored within a case base. After an experimental evaluation the experiences are structured by three main characteristics: the context of the equipment, the specific problem and the developed solution.

2. Case-Based Reasoning

Case-Based Reasoning (CBR) is a process to solve problems by adapting the solutions that were used to solve old problems [1]. A project appraiser who appraises a new project by remembering the previous solution similar problem and adopts that solution to the new project is using CBR. In fact, this occurs in our day-to-day activities when we frequently use reasoning from past experiences to solve problems. In the CBR process, the experiences gained through the previous cases are stored and merged with the general knowledge (some general rules and theories) for solving the new problem. CBR is also an approach for sustaining learning incrementally since a new experience is retained in the case-base or memory [2]. The general structure of a CBR system is shown in Figure 1. Here the general knowledge will be a basis for many solved cases and all together build a model for a CBR system. A new unsolved case is introduced into the model, and a new solution will be retrieved. A CBR system is able to read the unsolved case (as input data), and it retrieves the best similar solved case (as output data). The solution of the solved case will be suggested and approved for the unsolved case and a new solution will be derived. The new solution can be used directly in the new problem, or modified according to the differences between the input and output cases. The CBR machine can only contain cases without general knowledge (i.e. rules and theories). Such a case-base will be poor in the knowledge, and the assessment of similarity between unsolved and solved cases will be a simple process, just one by one attributes matching. On the other hand, the CBR model can be knowledge-rich and integrates general knowledge (theories and models) and cases. This type of CBR model is called the knowledge-intensive CBR model [2,3,4,5,6,7,8,9,10]. Such a model will be implemented in this study.

Whether the CBR model is lean or rich in knowledge, the CBR process can be explained in different steps within what is called the CBR cycle. Aamodt and Plaza introduced four steps for the CBR cycle as illustrated in Figure 1.

These processes are:

- Retrieving the most similar previously solved cases
- Reusing the retrieved cases by copying or integrating the proposed solution
- Revising or adapting the proposed solution
- Retaining the new generated solution for future use

Fig. 1 has been referred to and used in most of the CBR articles and papers. The detailed discussions and explanations for each step is given in these references [2,3,4,5,6,7,8,9,10].

2.1. Building a CBR Application

CBR process involves reading the attributes of a new unsolved case, matches it with the many solved cases which have been stored previously in the machine memory and retrieves the most similar solved case. Therefore, the output of the process is a proposed solution to the new unsolved case. Typically, the tool includes a variety of components for (a) constructing and maintaining a case base, (b) searching for and retrieving cases from the case base, and (c) a facility for augmenting case recommendations with expert-style rules. The creation of a case base begins with the establishment of the attributes of cases.

Cyclones are devices used for sizing, classification and screening of particulate materials in mixture with fluid (gases or liquid).

Cyclone sizes and shapes vanguard has no moving parts. The mode of operation involves the process of subjecting the flowing fluid to swirl around the cylindrical part of the device [11].

They impact the cyclone walls, full down the cyclone wall (by gravity) and are collected in a hopper. The most important parameter of a cyclone is its collection efficiency and the pressure drop across the unit.

Cyclone efficiency is increased through:

- Reduction of cyclone diameter, gas outlet diameter and cone angle;
- Increasing the cyclone body length.

Capacity is however increased by increasing the cyclone diameter, inlet diameter and body length

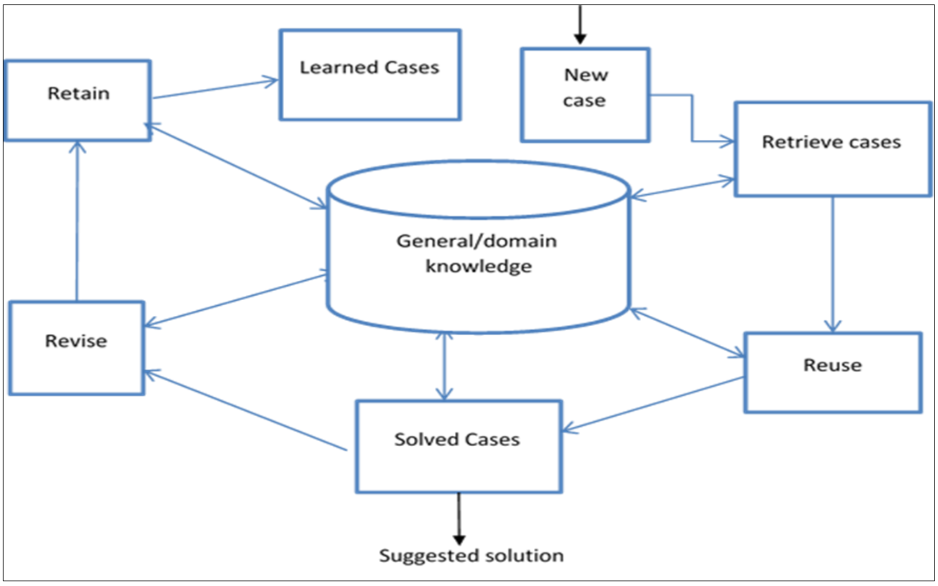

Figure 1 Cyclic process of CBR (from (Aamodt and Plaza, 1994))

Increasing the pressure drop give rise to;

- Increase in separation efficiency
- Higher capacity
- Decrease in the underflow to through part ratio
- Cleaner overflow

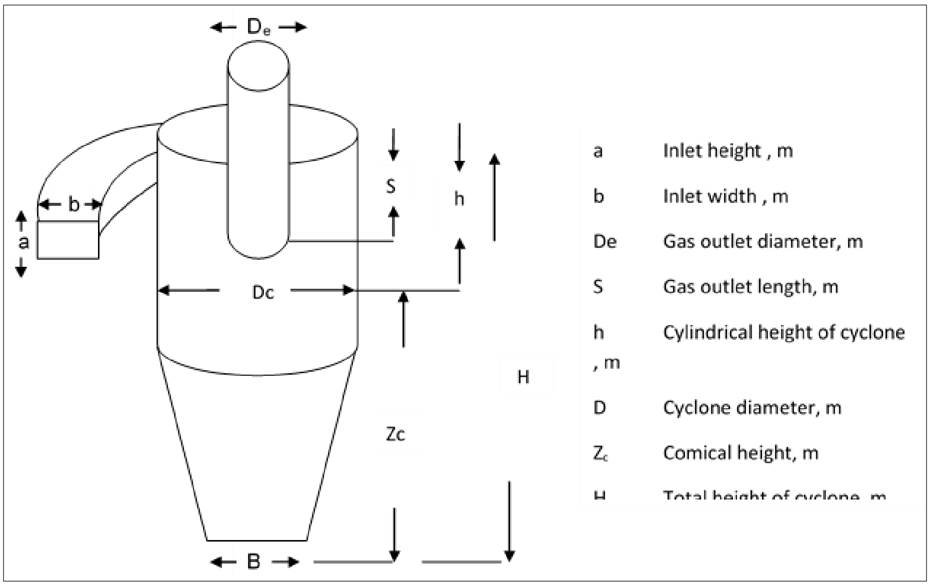

Figure 2 Design Parameters

The design parameters include:

- Feed rate, Q m^3/s
- Cyclone diameter D_c , m
- Set cut size d_{pc} , µm
- Cyclone efficiency
- Cyclone pressure Drop D_P
- Cyclone Geometry (Dc, h, H, c, b, B)
- Temperature ^oC
- Pressure, N/m^2
- Viscosity, Ns/m^2
- Density fluid, kg/m^3
- Mass Median Diameter MMD, (µm)
- Geometric Standard Deviation GSD, µm
- Number of Cyclones
- Fluid density, Kg/m^3
- Particle density, Kg/m^3

Table 1 displays the attributes of the cases used in this Gas Cyclone Design application. Attributes are similar in concept to fields and attributes used in database applications. However, the procedures used for retrieving cases are more robust than those that are used for database retrievals.

Table 1 Gas Cyclone Attributes

Example of case attributes	
Attributes	**Type**
Equipment Name	Text
Feed rate	Single
Pressure Drop	Single
Temperature	Single
Pressure	Single
Viscosity	Single
Fluid Density	Single
Mass Median Diameter MMD	Single
Geometric Standard Deviation GSD	Single
Number of Cyclone	Integer
Particle Density	Single
Required dimension of the Gas Cyclone	Single
Inlet height, a	Single
Inlet width, b	Single
Gas outlet diameter, De	Single
Gas outlet length, S	Single
Cylindrical height of cyclone, h	Single
Cyclone diameter, D	Single
Conical height, Zc	single
Total height of cyclone, H	Single
Dust outlet diameter, B	Single

In the retrieval step, the first step involves determining/matching the closest similar solved cases and retrieved. This step has been subdivided into three sub-steps; identify features, initially match, search and select executed in that order. Both solved and unsolved cases defined the CBR model as a set of descriptors (features).

2.2. Cases and their Attributes

The matching process has the ability to use rules similar to those in expert systems to aid in the completion of enquiries and to adapt retrieved cases to meet the search's objectives. A completion rule is used to identify special values in the search criteria and if these criteria are identified, a different weight is assigned to the attributes of that value. For example, the attribute for a equipment's pressure drop is a numerical range. Over a wide range of equipment pressure drop.

Table 2 Gas Cyclone input parameters

Example of case attributes	
Attributes	**Type**
Equipment Name	Text
Feed rate	Single
Pressure Drop	Single
Temperature	Single
Pressure	Single
Viscosity	Single
Fluid Density	Single
Mass Median Diameter MMD	Single
Geometric Standard Deviation GSD	Single
Number of Cyclone	Integer
Particle Density	Single

Levels, the precise value may not be significant. The rule-based system is normally used to identify the nearness of stored cases to the new problem, and it would assign a weight to this attribute which signify to closeness to the new problem. This would enable the retrieval to find more useful cases. String attributes allow the incorporation of free text of unlimited length within attributes. This is especially important for CBR systems, which draw on cases that are diverse in nature. Each new equipment poses a unique input parameters scenario and there are a number of different ways (terms) to describe the characteristics/ (attributes) of a potential project. For example, the attribute "What is the capacity estimate of the process equipment?" could be described in a number of different ways with varying degrees of detail. The advancements in CBR allow us to store and search cases in both textual (text files) and database (field) formats. The database format is chosen for illustrative purposes. Table 3 depicts an Access database with 7 cases (entries) with sample (not a comprehensive list) attributes (fields) structured to capture the input parameters. Table 2 is an example of a new case from which the relevant attributes were extracted (manually) and entered into the access database as a "case entry."

2.3. K-Nearest Neighbor and Retrieval Process

When one seeks to query the CBR application for cases similar to the needs of the user, the system provides prompts to which the user can respond. The application comes up with its best matches. Choosing to select or not to select certain attributes, allows for more meaningful retrieval and subsequent decision making. The next section discusses more ways to accomplish meaningful retrieval.

Distance is one of the concepts that is closely related to similarity. The greater the distance between a query and a stored case, the less the similarity between them. The main use of the similarity measurement in CBR is to sort the retrieved cases. From that backdrop, the similarity and distance measurements have an inverse relationship, and either of them may be chosen. Hence the distance measurement adopted in this research project, as defined by the following formula:

$$distance(q,c) = \sqrt{\frac{\sum_{i=1}^{n} \mathrm{wf_i df_i}^2(\mathrm{q_f}, \mathrm{c_f})}{\sum_{i}^{n} \mathrm{wf_i}}}$$

Where q, c, f, df and wf denote a query, a stored case, a particular feature and the weight for the feature f respectively.

In addition, df(q_f , c_f) is a function used to compute the difference between a query and a stored case on a feature f, which is defined as follows

$$\mathrm{dif}(qf\,,\,cf) = \begin{cases} |qf - cf| & \text{f is a numerical feature(normalized)} \\ 0 & \text{f is a nominal feature, and } qf = cf \\ 1 & \text{f is a nominal feature, and } qf \neq cf \\ 1 & \text{c or q has missing value on f} \end{cases}$$

This is *k*-nearest neighbor algorithm which is most basic algorithm for the description of relation between two cases. In these algorithms, an instance ***x*** is represented as a point in an *m*-dimensional space, ***x*** _ $(x_1 \ldots xm)T$, and the criteria consist of the standard Euclidean distance norm as a similarity metric and a discrete valued or real-valued target function for the classification assignment. When a new query instance is encountered, a set of example instances, near the query point, is selected based on the distance norm. An approximation to the target function is constructed over all these instances surrounding the query instance, which is then used as the estimated target value for the new instance, and classification of the new query instance is made accordingly. On the issue of similarity computation based on k-nearest neighbor, the critical challenges is how to assign weight to the feature that enable the most similar case to be identified by an index of the corresponding features. In order to address this problem, this research work develops a model which the k-nearest neighbor for similarity measuring and artificial neural network algorithm for feature weight assigning. Similarly, a brief look was also given to rule-based system for weight assigning but was disregarded because it requires complete knowledge elicitation [12].

3. Case-Based Reasoning System and Artificial Neural Network

3.1. Basic Frameworks

In this section, some representative network models and methods employed for building CBR systems are introduced. A common feature among these approaches is then summarized. In general, the parallel computing structures and neural network models used for CBR system design can be feature weighting optimization; the connection weights of the network can be learned through either supervised or unsupervised training procedures. A parallel computing network structure has been proposed for case-based reasoning. As shown in Fig. 3, the network is a feed-forward network with one hidden layer, and for a new query, is designed to make a specific choice, or a design decision, based on a set of stored cases. A problem under consideration is viewed as a point in an *m*-dimensional feature space which determines the number of input nodes in the net- work.

Each hidden node and output node represent an old case and a specific decision choice, respectively. The components or attributes of the problem feature vector are characterized by two types which are related to the activation level of hidden nodes. With a predetermined weight between each two nodes, the hidden and output layers are fully connected. Such a connecting weight suggests a measure to which a stored case is relevant to a specific design choice. When a new query problem is presented to the network, the value of each attribute in the given problem feature vector is detected. On this basis, a set of hidden nodes is excited (i.e. a set of old cases is retrieved), and then relating design choices are suggested. Note that the higher the activation level of an activated hidden node, the higher the degree of similarity between the new problem and the old problem contained in the retrieved old cases. Meanwhile, the old cases vote for different choices in proportion to their similarity degree to the new problem. In such a way, the network defines a mapping between problem and design choice, which is based on the experience and knowledge concerning the known design cases [13]. Additionally, by constructing different mapping forms, the network can be used as direct feature-based reasoning, case-based reasoning, and combined reasoning, respectively.

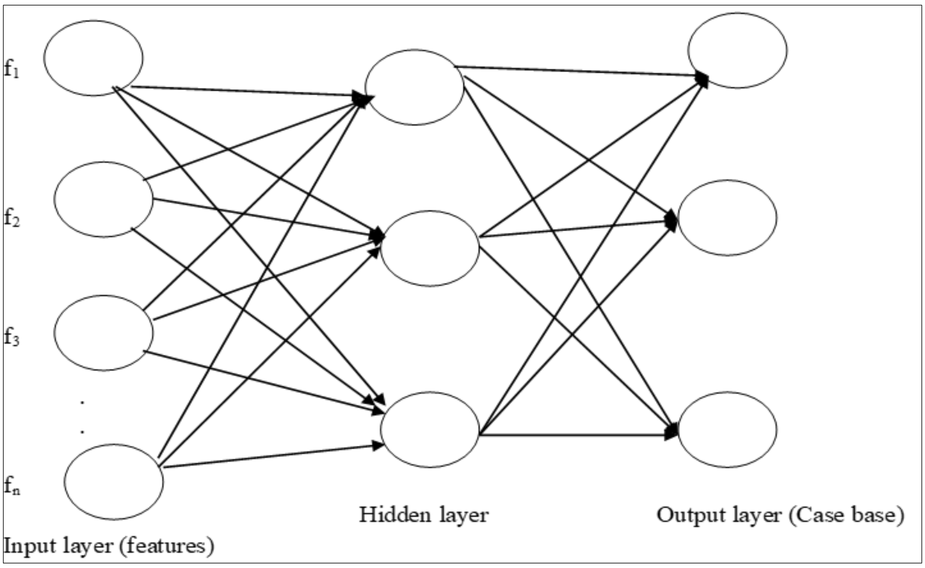

Figure 3 A Multi- layered neural network model for CBR

4. The CBR Model for Gas Cyclone Design

A cyclone is required to remove carbon dust particle from affluent air coming from a thermal power station at a rate of 4.5m^3/s at 64.5^{o}C. The dust particles are assumed to have normal size distribution with MMD of 20.5µm and GSD of 1.5µm. For energy cost consideration the pressure drop in the cyclone is required to be not more than 1000 N/m^2. The density of the dust particle is 2248kg/m^3 and cyclone operating at atmospheric pressure.

What is the required size and cut size of the cyclone that you will recommend?

Q = 4.5m^3/s, Temp = 64.5^{o}C, MMD = 20.5µm GSD 1.5µm

Pressure 1500 N/m^2 ρ dust particle 2248kg/m^2

This study develops a CBR model for Gas Cyclone Design based on features of the similar equipment already designed (case). The process of proposed CBR model in the first stage, features and design parameters of the equipment and their scale are identified.

In the next stage, the CBR-based model is developed for retrieval of past similar cases. Methods of calculating feature weight, feature distinction, case distinction, and adaptation can be different according to viewpoint of researcher's who is developing the CBR model.

The highlights on its input parameters are given as follows:

Feed Rate= 4.5m^3/s
Pressure Drop, D_P=1000.0 N/m^2
Temperature = 64.5^{o}C

Pressure =1500.0 N/m^2
Viscosity=1248kg/ms
Fluid Density=2248kg/m^2

MMD = 20.5µm

GSD=1.5µm

Cyclone diameter =1.586m

At the present study, we show the application of CBR method for design of the 4.5m^3/s Gas Cyclone equipment. A case-base is made with 7 cases (projects) and is shown in Table 3.

Table 3 Case Bases

Gas Cyclone Input Data										
Equipment Name	**Equipment No**	**Feed Rate**	**Pressure Drop**	**Temp-erature**	**Pressure**	**Viscosity**	**Fluid Density**	**MMD**	**GSD**	**Number Of Cyclone**
Gas Cyclone	AfGC01	5	1000	65	2000	625	2250	20	2	1
Gas Cyclone	AfGC02	10	1500	75	2200	635	2150	30	4	2
Gas Cyclone	AfGC03	7	800	55	2300	645	2050	25	3	1
Gas Cyclone	AfGC04	6	500	85	2400	655	1950	20	2	2
Gas Cyclone	AfGC05	9	800	95	2400	600	1850	40	2	1
Gas Cyclone	AfGC06	4	1100	65	2100	665	2350	35	6	3
Gas Cyclone	AfGC07	3	1200	35	1900	725	2250	27	2	1

Table 4 Cyclone Dimension

Cyclone Dimension									
Equipment No	**Inlet height**	**Inlet width**	**Gas outlet diameter**	**Gas outlet length**	**Cylindrical height of cyclone**	**Cyclone diameter**	**Conical height**	**Total height of cyclone**	**Dust outlet diameter**
AfGC01	0.5	0.25	0.5	0.625	2	2	4	6	0.25
AfGC02	0.25	0.15	0.55	0.725	3	2.5	4.4	6.6	0.35
AfGC03	0.35	0.45	0.65	0.425	2.5	2	5.4	6.2	0.45
AfGC04	0.45	0.25	0.75	0.325	2.2	3.2	3.4	6.3	0.55
AfGC05	0.55	0.35	0.85	0.425	3.5	4.2	2.4	6.4	0.55
AfGC06	0.65	0.55	0.95	0.525	3.2	2.2	1.4	5.6	0.65
AfGC07	0.75	0.55	0.45	0.625	2.2	1.2	4.5	7.6	0.75

4.1. The Search Process

The search process is initiated with the entry (by selecting the relevant attributes) of the partial description of a new project. This application uses the description to identify and rank potentially matching cases in the case base. It is possible that exactly the right client description can be located, however, that is rarely the case. The programmer has the power to program the search process to use the attributes in different ways and entered in response to the questions derived from the cases, all of the cases are re-ranked. Table 5 displays an example of a set of results produced by a query. Note that the example provided does not provide comprehensive list of attributes (corresponding to each case) or cases retrieved. A comprehensive list of attributes and cases would ordinarily be displayed for re use and analysis. The retrieved set of results gives the user a description of the original case, the attributes associated with it, and the closest matching cases. The application can be made to adapt the recommended case automatically or prompt the user to adjust for the adaptation rules.

Table 5 Retrieved Cases

Gas Cyclone Input Data										
Equipment Name	**Equipment No**	**Feed Rate**	**Pressure Drop**	**Temp erature**	**Pressure**	**Viscosity**	**Fluid Density**	**MMD**	**GSD**	**Number Of Cyclone**
Gas Cyclone	AfGC01	5	1000	65	2000	625	2250	20	2	1
Gas Cyclone	AfGC02	10	1500	75	2200	635	2150	30	4	2
Gas Cyclone	AfGC03	7	800	55	2300	645	2050	25	3	1
Gas Cyclone	AfGC04	6	500	85	2400	655	1950	20	2	2
Gas Cyclone	AfGC05	9	800	95	2400	600	1850	40	2	1
Gas Cyclone	AfGC06	4	1100	65	2100	665	2350	35	6	3
Gas Cyclone	AfGC07	3	1200	35	1900	725	2250	27	2	1

5. Using the Case-Based Process Equipment Design System (CBPEDS)

This section illustrates the general procedures to realize the implementation of the software, and attempt would also be made to highlight the use of the software to solve process equipment design problem. After a thorough review of different programming language, a Visual Basic Net was used for the development.

The general procedure for the program development is as follows: -

- System design and implementation
- Design the flows charts
- Develop program code in Visual Basic .Net

Essentially, Visual Basic (Window application) aspect of .net in conjunction with aforementioned tools was extensively in this software (CBPEDS).

5.1. Stating the software

To launch the software double, Click on CBPEDS icon on your desktop or CBPEDS sub menu on your program menu. This launches the splash screen as depicted by the interface as shown in Fig 4

Figure 4 Splash screen

After a while, a window shown in Fig 5 appears and button OK is clicked

Figure 5 About project Appraisal Software

Having clicked OK, the target case interface is displayed as shown in Fig 6. On the interface, choose the desired retrieval algorithm of your choice from the combo box among the following:

- K-nearest neighbor
- Artificial neural network
- Provide all necessary information as shown in Fig 6, click save and then next

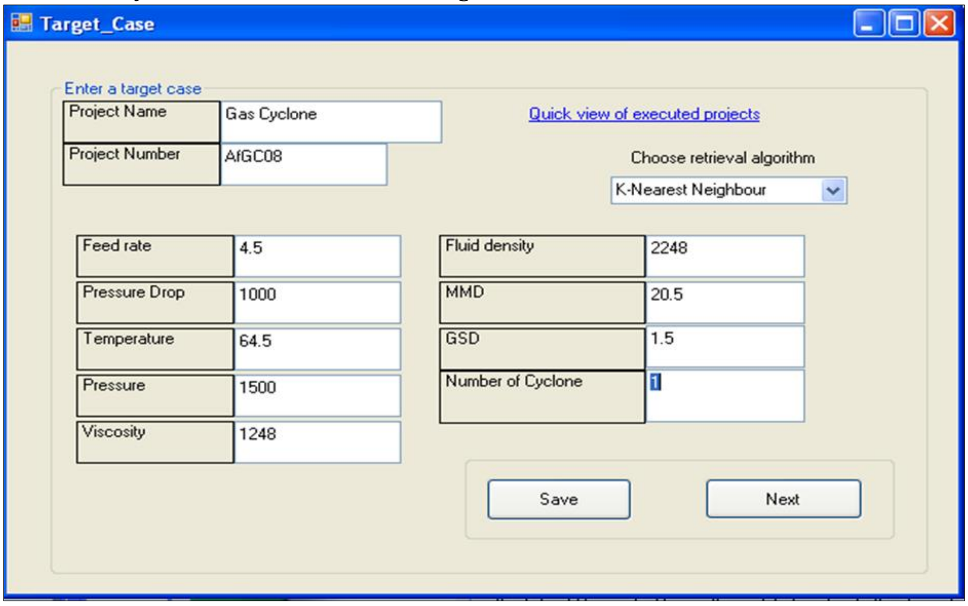

Figure 6 Target case interface

If k-nearest neighbor algorithm is selected, Fig 7 is displayed. To retrieve the most similar case, click retrieve case submenu from the File menu.

The results are displayed in the datagrid controls. The first datagrid displays all the relevant cases while the second datagrid shows the most similar case. The third datagrid shows the dimension of the gas cyclone.

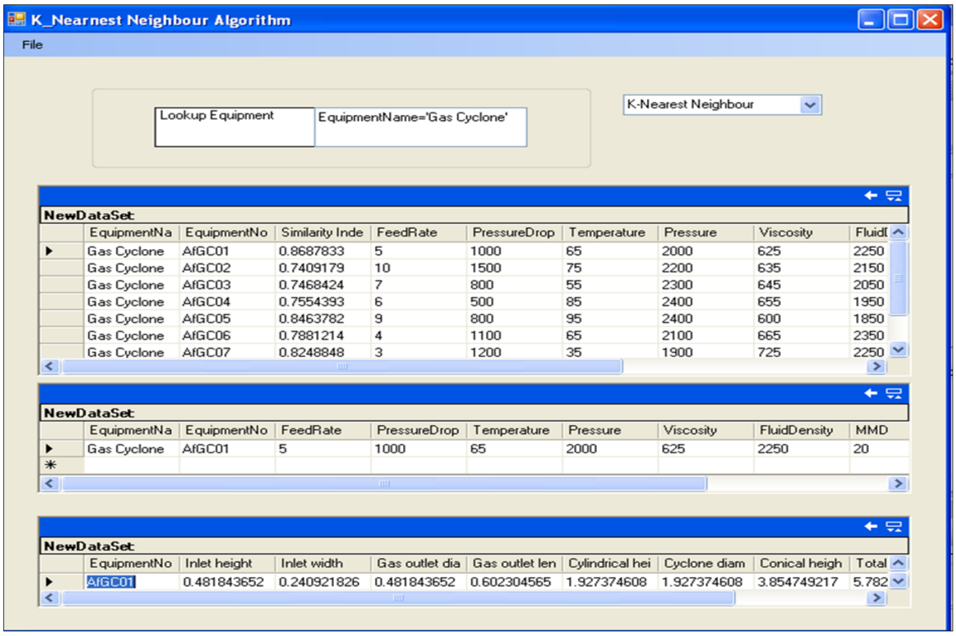

Figure 7 K-Nearest Neighbour interface

Having retrieved the most similar case, re-use sub menu is clicked and the required dimension of the gas cyclone is displayed in the third datagrid.

6. Results and Discussion

The target case used for testing are as shown in Table 6. The predicted result is as shown in Table 7. We observe from these results retrieved using k-nearest neighbor algorithm that the AfGC01 has highest similarity index of 0.8687933. Therefore, the predicted cyclone dimensions (as ratio of cyclone diameter, D_c) are:

Inlet height, a_o =0.48

Inlet width, b_o =0.24

Gas outlet diameter, De_o =0.48

Gas outlet length, S_o =0.6023

Cylindrical height of cyclone, h_o = 1.93

Cyclone diameter, D_c =1.93

Comical height, Zc_o = 3.86

Total height of cyclone, H_o = 5.78

Dust outlet diameter, B_o = 0.25

The similarity Index is 86.9% using 7 gas cyclones sample cases shown in Table 3.

7. Conclusion

This paper shows that CBR is a promising tool for solving process equipment design problems if previous cases are available. In the developed CBPEDS system, the most impressive capability demonstrated is that it can retrieve previous cases by various numbers of input features. It is then concluded that CBR is helpful when knowledge is incomplete, or evidence is sparse; a CBR approach is obviously superior to traditional expert systems in this aspect. The basic function of CBR approach is retrieving of previous cases based on which the current problem is solved. How the previous cases are retrieved from the case base is the most important thing and needs most consideration for a successful CBR application. When developing a CBR application, features of a case base as well as the features' weights for matching need to be defined carefully. If they are not defined properly, the retrieved cases may not be the ones leading to correct solutions. From the case study shown in this paper, we can conclude that CBR approach is one of the acceptable alternatives for fast process equipment design. This is mainly due to the experience driven nature of equipment design activities and the ability of CBR approach to mimic the decision making of the design engineers.

The CBPEDS is a pilot system for integrating CBR approach into the equipment design domain. To validate the system, test of a real and comprehensive design project is needed in the future.

Other computer technologies such as neural networks, genetic algorithm may also be incorporated into the CBR system to enhance its problem-solving capability.

Compliance with ethical standards

Acknowledgments

The authors thank the support of Raw materials Research and Development Council, (RMRDC) for materials used in this paper. This material is based on research sponsored by RMRDC. The Council authorized us to reproduce and distribute reprints for reference purposes notwithstanding any copyright notation thereon.

Disclosure of conflict of interest

No conflict of interest.

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