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Design and Development of a Decision Support System for Safety Management of Rotary Pump Systems

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Abstract: Increasing technological advancement and complexity have made it necessary to develop more effective approaches to safety, reliability and quality. This paper presents the design and development of decision support system for safety management of rotary system using computational intelligent techniques. The rotary system considered for this research paper is centrifugal pumping system. This paper presents the application of Neural Network approach for fault detection and fuzzy logic approach for fault diagnosis in centrifugal pumping system. This paper highlights the development of decision support system integrating all the subsystem for a real-world application of computational intelligent techniques to solve a complex problem, which contributes to the prevention of accidents and preparation for emergency response. The results are compared and the conclusions are presented which demonstrate the possible application of industrial use.

Keywords: Decision support system, Fault detection, Fault diagnosis, Neural Networks, Fuzzy Logic

1. INTRODUCTION

With industrial development the industrial risk problem and the diversification of risk types have increased concurrently. At the same time, the risk acceptability threshold of the population has decreased. The increasing diversity of products manufactured by process industries has made to use pressure vessels, reactors, and storage vessels in which hazardous substances are handled at elevated temperature and/or pressure. Accident in such units caused either by material failure; operational mistakes or external perturbation can have serious and often catastrophic consequences. Along with the rapid growth of industrialization and population, the risk posed by probable accidents also continues to rise.

Increasing technological advancement and complexity have made it necessary to develop more effective approaches to safety. This need is particularly strong in the design, operation and maintenance of process plants. Traditionally, safety in the design, operation and maintenance of process plants relied upon the application of codes of practice, design codes and checklists based on the wide experience and knowledge of professional experts and specialists in the industry. However, such approaches can only cope with problems that have arisen before.

Process and chemical industries are the critical industries, which required a number of safety related issues to be addressed. Generally organizations face the difficult task of making risk management decisions on the basis of qualitative results from many hazard evaluation studies particularly with respect to critical safety areas. So managers and other higher officials need help in putting this vast amount of largely subjective information into perspective. In addition to that, the plants are designed to operate safely under normal conditions; however improper operation can lead to equipment failure and release of potentially hazardous materials. This necessitates continuous monitoring of various parameters of the plant on real time basis. The operators and supervisors in the plant, given enough time, might be able to analyze the large volume of data in real time collected from many critical systems for features indicative of faults or other safety related features. They use the conventional methods of manually processing the vast amount of knowledge available in the form of various documents about the various malfunctions that can occur. This is not suitable when the plant is under operation or under emergency. Also, it is impractical to expect the operator to perform this sort of monitoring and diagnosis continuously. Under this condition, it may be of great use if an automated system is developed for real time as a monitoring of the plant.

Due to the broad scope of the process fault diagnosis problem and the difficulties in its real time solution, many analytical based techniques have been proposed during the past several years for the fault detection of technical plants [1,2]. The important aspect of these approaches is the development of a model that describes the 'cause and effect' relationships between the system variables using state estimation or parameter estimation techniques. The problem with these mathematical model based technique is that under real conditions, no accurate models of the system of interest can be obtained. In that case, the better strategy is of using knowledge-based techniques where the knowledge is derived in terms of facts and rules from the description of system structure and behavior. Classical expert systems were used for this purpose. The major weakness of this approach is that binary logical decisions with Boolean operators do not reflect the gradual nature of many real world problems.

Recently with development of artificial intelligence, Computational Intelligence (CI) methods (Neural Networks (NN), Fuzzy Logic (FL), Evolutionary Algorithms (EA) , etc., more and more fault diagnostic approaches have emerged as new techniques for fault diagnostic systems [3,4,5]. All of those approaches are mainly generalized to three classifications: model-based diagnosis, algorithm based diagnosis and rule-based diagnosis. Model-based diagnosis concerns the knowledge, the so-called "deep knowledge" about the structures, functions and behaviours of diagnostic objects. For large and complicated rotating machines, this kind of knowledge is elaborate to acquire and employ. Algorithm-based diagnosis has the merit of integrating the knowledge into algorithm and is suitable for real-time application. Its main deficiency is the difficulty of modification and extension of knowledge. And rule-based diagnosis principally makes use of the heuristic knowledge, the so-called "shallow knowledge" of expert, having the characteristics of explicit knowledge description, simple reasoning mechanism and high effectiveness of acquiring solutions. Yet, the uncertainty, imprecision, incompleteness and difficulty in acquiring knowledge are its primary shortages.

Fuzzy Logic (FL) based techniques [6,7] have been proposed to develop fault diagnostic systems. Building a model for fault diagnosis involves embedding the heuristic knowledge inherent in the decision-making abilities of the human experts. Human beings acquire heuristic knowledge by experience and observations over a period of time. This knowledge has inherent fuzziness because it comes from uncertain and imprecise nature of expressing the abstract thoughts. Fuzzy logic can afford the computers, the capability of manipulating abstract concepts commonly used by the humans in decision-making. The advantage of fuzzy logic-based approach is that it gives possibilities to follow human's way of fault diagnosing and to handle different information and knowledge in a more efficient way. One of the most important considerations in designing any fuzzy systems is the generation of the fuzzy rules as well as the membership functions for each fuzzy set. In most existing applications, the fuzzy rules are generated by experts in the area, especially for fault diagnosis problems with only a few inputs. With an increasing number of variables, the possible number of rules for the system increases exponentially, this makes it difficult for experts to define a complete set for good system performance.

Artificial Neural Network based methods for fault diagnosis has received considerable attention over the last few years [8.9]. The advantage of the neural network approach is their generalization capability which lets them deal with partial or noisy inputs. The neural networks are able to handle continuous input data and the learning must be supervised, in order to solve the fault detection and diagnosis problem. The multilayer perceptron network is the most common network today. Due to their powerful nonlinear function approximation and adaptive learning capabilities, neural networks have drawn great attention in the field of fault diagnosis. But the neural network approach needs lot of data to develop the network before being put to use for real time applications. This paper deals with the design and development of decision support system for safety management of centrifugal pumping system using soft computing techniques such as artificial neural networks and fuzzy logic.

The paper is organized as follows: in the next section, the description of the experimental system for this study is outlined. Sections 3 describe the review of safety management tools and soft computing techniques. Sections 4 demonstrate the framework for decision support system and the development of various components/subsystems with detailed discussions on simulation results and finally, in Section 5, conclusions are drawn from the work.

2. SYSTEM DESCRIPTION

The pump is a mechanical device by means of which liquid may be conveyed from one place to the other. The nature of the liquids that are pumped varies from the most volatile fluid to the thick mud and sludge, from water to the most corrosive acids and alkalis, from fluids at low temperature to many types of molten metals. Pumping means addition of energy to a liquid to move it from one place to the other and this is done by means of piston, plunger, impeller, propeller, gears, screws, etc. The pump may be classified, according to the principle of operations into four general classes namely reciprocating pump, centrifugal pump, rotary pump and jet pump. The system selected for this research study is centrifugal pumping system.

A pump which employs centrifugal force for conveying liquids from one place to the other is called a centrifugal pump. The basic principle on which a centrifugal pump works is that when a certain mass of liquid is made to rotate by an external force, it is thrown away from the central axis of rotation and a centrifugal head is imparted which enables it to rise to a higher level. Here kinetic energy of the leaving water from the impeller is converted into potential energy which is utilized to increase the delivery head of the pump. In addition to the centrifugal action, as the liquid passes through the revolving wheel or impeller, its angular momentum changes, this also results in increasing the pressure of the liquid. Finally the diffuser casing increases the pressure at the expense of kinetic energy of the liquid.

The arrangement of the centrifugal pumping system is shown in Figure 1. The pump is connected to the motor through shaft. The voltmeter (0-600V) and ammeter (0-15A) are serially connected with the autotransformer (2Ω, 0-270V) and in turn with energy meter. Auto transformer is used to vary the voltage and current supplied to the motor. Energy meter is used to measure the input energy applied to the pump. Vacuum gauge and pressure gauge are fitted in the suction and delivery side. By using this, suction pressure and delivery pressure can be measured. This delivery pressure is the measure of head developed in the system. Collecting tank with flow meter is provided for measuring volume discharge delivered in the system.

The first step in the operation of a centrifugal pumping system is priming. Priming is the operation in which the suction pipe, casing of the pump and the portion of the delivery pipe upto the delivery valve are completely filled with the liquid which is to be pumped, so that all the air (or gas or vapour) from this portion of the pump is driven out and no air pocket is left. It has been observed that even the presence of a small air pocket in any of the portion of pump may result in no delivery of liquid from the pump. After the pump is primed, the delivery valve is still kept closed and the electric motor is started to rotate the impeller. The delivery valve is kept closed in order to reduce the starting torque for the motor. The rotation of the impeller in the casing full of liquid produces a forced vortex which imparts a centrifugal head to the liquid and thus results in an increase of pressure throughout the liquid mass. The increase of pressure at any point is proportional to the square of the product of angular velocity and the distance of the point from the axis of rotation. When the delivery valve is opened the liquid is made to flow in an outward radial direction thereby leaving the vanes of the impeller at the outer circumference with high velocity and pressure.

A pump is usually designed for one particular speed, flow rate and head, but in actual practice the operation may be at some other condition of head or flow rate, and for the changed conditions the behaviour of the pump may be quite different. In order to predict the behaviour and performance of a pump under varying conditions, real time simulation tests are performed in the experimental setup.

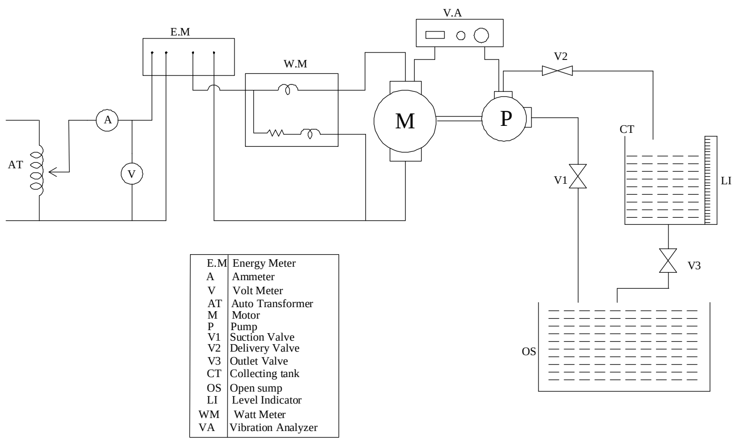


Figure 1 Schematic layout of the centrifugal pumping system

The seven numbers of probable fault categories are simulated in the system in real-time in the experimental setup. Table 1 shows the fault description with its corresponding code.

Table 1 Centrifugal pumping system fault description

S.No.	Fault category	Fault Description
1.	FC-A	Shaft problem
2.	FC-B	Bearing problem
3.	FC-C	Leakage Problem
4.	FC-D	Coupling problem
5.	FC-E	Impeller problem
6.	FC-F	Operability problem
7.	FC-G	Vibration

3. REVIEW OF TOOL AND TECHNIQUES USED

3.1 SAFETY MANAGEMENT TOOLS [10,11]:

HAZOP study identifies the possible ways in which the system could fail. It is a systematic technique for identifying hazards or operability problems associated with the plant installations. Each segment of the selected transfer sections was analyzed and all deviations from normal operating conditions and the mode of their occurrence examined.

Identification of the individual hazards, problems that could occur during the startup, normal operation, normal and emergency shutdown consequences of hazards, probability of their fructifying given the safety protection available have been the major objectives of the study.

The HAZOP analysis requires accurate, up-to-date Process Flow Diagrams or equivalent drawings, and other detailed process information, such as operating procedures.

Failure Modes and Effect Analysis (FMEA) evaluates the ways equipment can fail (or be improperly operated) and the effects these failures can have on a process. These failure descriptions provide analysts with a basis for determining where changes can be made to improve a system design. During FMEA, hazard analysts describe potential consequences and relate them only to equipment failures; they rarely investigate damage or injury that could arise if the system operated successfully.

3.2 FUZZY LOGIC

Fuzzy logic [12] was first developed by Zadeh in the mid 1960's to provide a mathematical basis for human reasoning. Fuzzy logic uses fuzzy set theory, in which a variable is a member of one or more sets, with a specified degree of membership. Fuzzy logic when applied to computers, allows them to emulate the human reasoning process, quantify imprecise information, make decisions based on vague and incomplete data, yet by applying a "defuzzification" process, arrive at definite conclusions.

Two common sources of information for building fuzzy models are the priori knowledge and data. The priori knowledge can be of a rather approximate nature (qualitative knowledge, heuristics), which usually originates from "experts". Data are available as records of the process operation or special identification experiments can be designed to obtain the relevant data. With regard to the design of fuzzy models, two basic items are distinguished: the structure and the parameters of the model. The structure determines the flexibility of the model in the approximation of (unknown) mappings. The parameters are then tuned (estimated) to fit the data at hand.

To design a (linguistic) fuzzy model based on available expert knowledge, the following steps can be followed:

- Select the input and output variables, the structure of the rules, and the inference and defuzzification methods.
- Decide on the number of linguistic terms for each variable and define the corresponding membership functions.
- Formulate the available knowledge in terms of fuzzy if-then rules.
- Validate the model (typically by using data). If the model does not meet the expected performance, iterate on the above design steps.

The following subsections present the various components of a fuzzy logic system.

Fuzzy sets

Fuzzy set theory generalizes classical set theory to allow partial membership with a smooth boundary. The degree of membership in a set is expressed by a number between 0 and 1. 0 means entirely not in the set, 1 means completely in the set, and a number in between means partially in the set. Mathematically, a fuzzy set A in the universe of discourse X is defined to be a set of ordered pairs,

$$A = \{(x, \mu_A(x)) \mid x \in X\} \qquad (1)$$

Where $\mu_A(x)$ is called the membership function of x in A. The parameterizable membership functions most commonly used in practice are the triangular membership function and the trapezoidal membership function. The former has three parameters [a, b, c] as follows:

$$\text{Triangle}(x: a, b, c) = \begin{cases} 0 & x < a \\ (x-a)/(b-a) & a \le x \le b \\ (c-x)/(c-b) & b \le x \le c \\ 0 & x > c \end{cases} \qquad (2)$$

Whereas the latter has four parameters [a, b, c, d] as follows:

$$\text{Trapezoid}(x: a, b, c, d) = \begin{cases} 0 & x<a \\ (x-a)/(b-a) & a\le x<b \\ 1 & b\le x<c \\ (d-x)/(d-c) & c\le x\le d \\ 0 & x\ge d \end{cases} \qquad (3)$$

Fuzzy if-then rules:

In the fuzzy rule-based system, the relationships between variables are represented by means of fuzzy if-then rules of the form:

If x is A_i then y is B_i, I = 1, 2, 3 …k

Where x is the antecedent variable, which represents the input to the fuzzy system, and y is the consequent variable representing the output of the fuzzy system. A collection of such rules, replace the usual mathematical model of system theory. The knowledge required to formulate the fuzzy if-then rules can be derived from a human expert or by an off-line simulation.

Fuzzy Inference System:

Inference in fuzzy rule-based system is the process of deriving an output fuzzy set given the rules and the inputs. The max-min or Mamdani inference, which is followed in this paper, is summarized below:

Step 1: For each rule I, the degree of fulfillment

β_i of the antecedent is computed as

$$\beta_{i} = \mu_{Ai1}(x_1) \wedge \mu_{Ai2}(x_2) \wedge \ldots \wedge \mu_{Aip}(x_p)$$

Step 2: The output fuzzy set B_i^1 is derived for each rule, using the minimum t – norm

$$\mu_{Bi}^{1}(y) = \beta_i \wedge \mu_{Bi(y)} \qquad ¥ \; y \in Y.$$

Step 3: The aggregated output fuzzy set is computed by taking the maximum of the individual conclusion B_i^1 :

$$\mu_B^{1}(y) = \max_{i=1,2,3,\ldots\ldots k} (\mu_{Bi}^{1}(y)) \quad ¥ \; y \in Y$$

Defuzzification:

The result of fuzzy inference is the fuzzy set B^1. If a numerical output value is required, the output fuzzy set must be defuzzified. Defuzzification is a transformation that replaces a fuzzy set by a single numerical value representative of that set. There are various methods line centroid method, weighted average method, max-membership method etc., for this purpose.

3.3 ARTIFICIAL NEURAL NETWORK

Neural networks [13,14] have recently attracted much attention based on their ability to learn complex, nonlinear functions. Neural networks have a variety of architectures, but the most widely used is the Feedforward network trained by backpropagation. Backpropagation networks have been applied to many pattern recognition problems including the classification of pattern, speech recognition, sensor interpretation, and failure state recognition in chemical processes. These are able to diagnose correctly with missing or faulty sensors, and diagnose multiple failures after training on single malfunctions.

Artificial Neural Networks can be viewed as parallel and distributed processing systems which consists of a huge number of simple and massively connected processors. These networks can be trained offline for complicated mapping, such as of determining the various faults and can then be used in an efficient way in the online environment. The MLP architecture is the most popular paradigm of artificial neural networks in use today. Fig.3 shows a standard multilayer feed forward network with three layers. The neural network architecture in this class shares a common feature that all neurons in a layer are connected to all neurons in adjacent layers through unidirectional branches. That is, the branches and links can only broadcast information in one direction, that is, the "forward direction". The branches have associated weights that can be adjusted according to a defined learning rule.

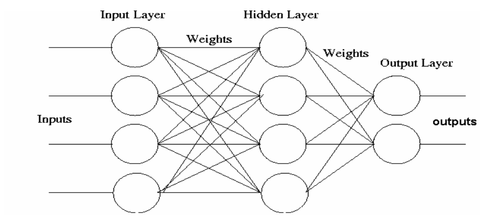


Figure 3. Feed forward network architecture

Feed forward neural network training is usually carried out using the back propagation algorithm. The back propagation network consists of several layers of nodes with adjacent layers exhaustively interconnected in the Feedforward direction by weighted connections. The network has N nodes in the input layer, one for each of the inputs x, and M nodes in the output layer, one for each of the possible classes y. Each node in subsequent layers takes a weighted sum across its inputs, applies a sigmoidal threshold function, and produces continuous output activation in the range [0, 1]. Training the network with back propagation algorithm results in a non linear mapping between the input and output variables. Thus, given the input/output pairs, the network can have its weights adjusted by the back propagation algorithm to capture the non linear relationship. After training, the networks with fixed weights can provide the output for the given input.

The standard back propagation algorithm for training the network is based on the minimization of an energy function representing the instantaneous error. In other words, it is desire to minimize a function defined as

$$E(m) = \frac{1}{2}\sum_{q=1}^{n}[d_q - y_q]^2 \tag{4}$$

where d_q represents the desired network output for the q^{th} input pattern and y_q is the actual output of the neural network. Each weight is changed according to the rule:

$$\Delta w_{ij} = -k\frac{dE}{dw_{ij}} \tag{5}$$

where k is a constant of proportionality, E is the error function and w_{ij} represents the weights of the connection between neuron j and neuron i. The weight adjustment process is repeated until the difference between the node output and actual output is within some acceptable tolerance. The algorithm for the training of artificial neural network model is given below:

Step 1:- Load the data in a file.
Step 2:- Separate the input and output data.
Step 3:- Separate the training and test data.
Step 4:- Normalize all the input and output values.
Step 5:- Define the network structure.
Step 6:- Initialize the weight matrix and biases.
Step 7:- Specify the number of epochs.
Step 6:- Train the network with the train data.
Step 7:- Test the network with the test data.
Step 8:- Re-normalize the results.

4. DECISION SUPPORT SYSTEM DEVELOPMENT

Any complex system is liable to faults or failures. A 'fault' is an unexpected change of the system functionality. It manifests as a deviation of at least one characteristic property or variable of a technical process. It may not, however, represent the failure of physical components. Such malfunctions may occur either in the sensors (instruments), or actuators, or in the components of the process itself. In all but the most trivial cases the existence of a fault may lead to situations related to safety, health, environmental, financial or legal implications. Although good design practice tries to minimize the occurrence of faults and failures, recognition that such events do occur, enables system designers to develop strategies by which the effect they exert is minimized. A system that includes the capability of detecting and diagnosing faults is called the 'fault diagnosis system' [15,16,17]. Such a system has to perform two tasks, namely fault detection and fault isolation. The purpose of the former is to recognize that a fault has occurred in the system. The latter has the purpose of locating the fault. The following are the set of desirable characteristics one would like the diagnostics system to possess: a) Quick detection and diagnosis b) Isolability c) Robustness d) Novelty identifiability e) Classification error estimate f) Adaptability g) Explanation facility. h) Modeling requirements i) Storage and computational requirements j) multiple fault identifiability.

Decision support system (DSS) is the area of the information systems discipline that is focused on supporting and improving managerial decision-making [18,19]. A DSS is an interactive, flexible, and adaptable, specially developed for supporting the solution of a non-structured management problem for improved decision making. It utilizes data, it provides easy user interface, and it allows for the decision maker's own insights. Fig.2 shows the proposed framework for the decision support system of safety management of centrifugal pumping system. The important components in the proposed decision support system are given below.

a. Data Management Subsystem:
   Contains and interrelates data from different sources to aid the decision-making process.

b. Model Management Subsystem:
   Software to help create models, data manipulation in models, update models, and create new routines in models

c. Knowledge-based subsystem:

It provides knowledge that can enhance the operations of each subsystem of a DSS

d. User Interface Subsystem:

It covers all aspects of communication between a user and the DSS. It is the interface to the user and consists of a GUI that is typically displayed via a browser

e. The User:

Two major classes - managers (users or decision makers) and intermediaries

(Staff assistant, Operating personnel, Expert tool user, Business (system) analyst etc.,)

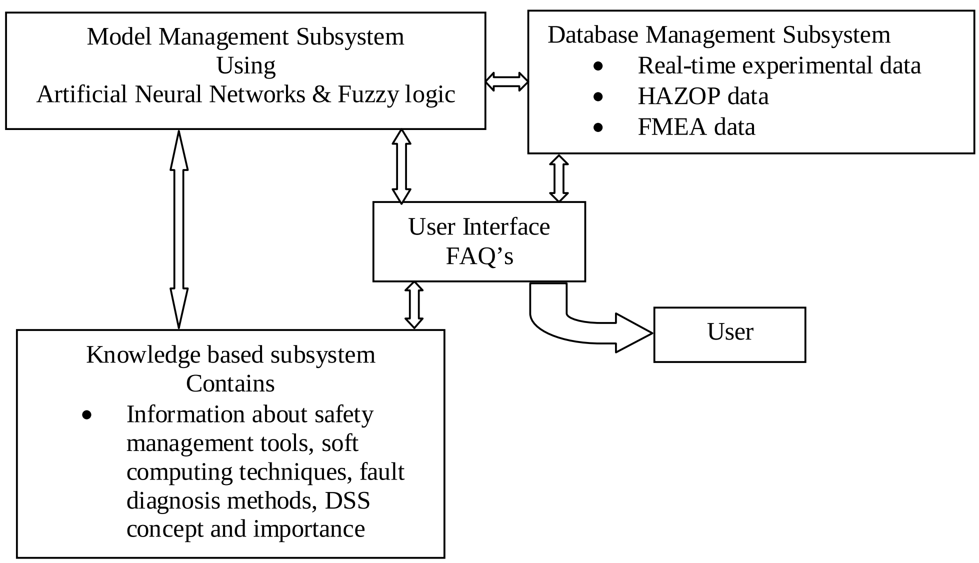


Fig. 2. Proposed DSS framework for safety management in centrifugal pumping system

4.1 NEURAL NETWORK MODEL DEVELOPMENT AND RESULT SIMULATION

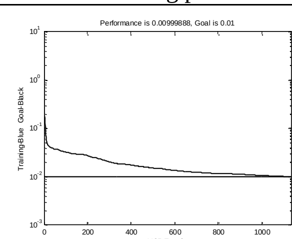
The proposed methodology for fault detection in centrifugal pumping system is based on using Artificial Neural Network (ANN) for detecting the normal and abnormal conditions of the given parameters, which lead to various faults. The normal condition represents no fault situation and abnormal condition represents, fault occurrence. The main purpose of selecting ANN as a tool is inability to form a mathematical relationship due to the nonlinearity between the inputs and the outputs, good generalization ability, fast real time operation, simple online control and to perform the complicated mapping without functional relationship.

The neural network approach for this purpose has two phases; training and testing. During the training phase, neural network is trained to capture the underlying relationship between the chosen inputs and outputs. After training, the networks are tested with a test data set, which was not used for training. Once the networks are trained and tested, they are ready for detecting the fault at different operating conditions.

The following issues are to be addressed while developing the model for fault detection in centrifugal pumping system are a) Selection of input and output variables, b) Training data generation, c) Data normalization, d) Selection of network structure and e) Network training.

The generated training data are normalized and applied to the neural network with corresponding output, to learn the input-output relationship. The neural network model was trained with the matlab program using the neural network toolbox. Based on the developed matlab program, the feed forward neural network model is trained using the back propagation method. At the end of the training process, the model obtained consists of the optimal weight and the bias vector. After training the generalization performance of the network is evaluated with the help of the test data and it shows that the trained ANN is able to produce the correct output even for the new input. After training the network with least error rate, the testing data was fed as input to the network. The testing data comprises of both normal and abnormal data. The output performance result from the network is given in Table 2. This shows that the trained neural network model is able to produce the correct output even for the new input.

Table 2. Performance *of the neural network model*

Description of parameters	Performance details	Network training performance
Number of Hidden Layers	2	
Number of Hidden nodes	14 X 15	
Functions used	Tansigmoidal	
Number of attributes	11	
Training Time	85.2650 seconds	
Mean Square Error during Training	0.0100	
Mean Square Error during Testing	0.0116	
Number of epochs	1135	
Percentage of classification	99.3%	

4.2 FUZZY LOGIC MODEL DEVELOPMENT AND RESULT SIMULATION

Fault diagnosis is a classical area for fuzzy logic applications. Compared to algorithmic approaches, the advantage of fuzzy logic-based approach is that it gives possibilities to follow human's way of fault diagnosing and to handle different information and knowledge in a more efficient way. This section presents the details of the fuzzy logic based diagnostic system developed for Centrifugal pumping system. The information required for the development of the fuzzy system was collected from the literature reference and field experts. The collected information includes the fault-symptom relationship for centrifugal pumps and the ranges of the variables. The objective here is to capture the implicit knowledge behind the diagnosis process, which is embedded in the information collected from the experts, through the developed model so that it can be applied for the diagnostic process when the system is in operation. According to the expert's view, whenever some fault occurs on some part of the system, this is reflected in the form of changes in the values of Temperature, Pressure or Flow of the operating liquid. Hence these variables are taken as the input of the developed fuzzy model. The input variables along with the operating range are given in Table 3. Membership functions were formed for all the input variables based on their values during the normal and abnormal conditions. In all the cases, triangular and trapezoidal functions were used and each variable was categorized into three fuzzy subsets. For illustration the membership function ranges formed for the input variables are shown in Table 4.

Table 3. Input variables with operating range

S.No.	Variables	Minimum value	Maximum value
1.	Pressure (kgf/cm^2)	30	470
2.	Flow (m^3/Sec)	0.072	8.00
3.	Temperature (deg. C)	Constant Atmospheric temperature	

Table 4. Membership Function Ranges

Flow (m^3/Sec)		Pressure(kgf/cm^2)	
Flow (High)	3.01 to 8.00	Pressure (High)	200 to 470
Flow (Normal)	0.45 to 3.00	Pressure (Normal)	71 to 199
Flow (Low)	0.072 to 0.449	Pressure (Low)	30 to 70

The various fault categories which are considered in the centrifugal pumping system are shaft problem, bearing problem, leakage problem, coupling problem, impeller problem, operability problem and vibration problem. The expert knowledge relating the symptoms and the various faults are formulated in the form of fuzzy if-then rules. A set of such rules constitutes the rule base of the Fuzzy Inference System. This form of knowledge representation is appropriate because it is very close to the way experts themselves think about the diagnosis and decision process.

The description of the rule structure is given as:

IF Flow is more AND Pressure is more THEN the fault class/category is ----

The fuzzy rule matrix along with the membership functions will help to identify the potential faults present in the system. In order to obtain the global information concerning each fault represented by the interconnection of its causal chains via AND connectives, is used as an aggregation support. By placing the AND connectives with their isomorphical fuzzy operators (T-norms), the confidence level is extracted which combines the distinct pieces of information concerning fault's existence from each column into a global fault possibility. As fault class with particular threshold is considered, for the setting of threshold compromises have to be made between the detection of fault class and unnecessary false alarms because of normal fluctuations of the variables. In order to validate the diagnostic hypothesis according to which fault class may explain the system abnormal behavior the global possibility of the fault class has been projected within an implicit act of backward reasoning on the respective column of the fuzzy diagnostic model.

The fuzzy model was developed using MATLAB programming. While developing the fuzzy model *min* was used for *T-norm*, *max* was used for *T- conorm* and Mamdani inference was used. The developed model was tested with a number of test data collected from the system.

4.3 INTEGRATION OF DEVELOPED MODEL WITH OTHER COMPONENTS OF DSS

Finally the developed models are integrated in such a way that the detection is carried out by Neural Network model and diagnosis by Fuzzy Model. The input features taken from the experimental study are voltage reading (V), ammeter reading (A), vacuum guage reading (h_1), pressure guage reading (h_2), speed (N), time for h metre rise in the collecting tank (t) and the time for number of revolution in energy meter (N_e), total head, discharge, input power to the pump and output power of the pump, which are fed to the ANN model. The binary value of normal and abnormal is taken as the output. The output of ANN model is that it specifies whether the inputs are in normal operating range or not. If they are in abnormal range then inputs are fed to Fuzzy model. The output of the Fuzzy model specifies the confidence level of each fault that is about to occur in that operating range. Of all the faults occurred the one with high confidence value is considered as critical and the details of that fault with its causes, consequences and remedial measures will be given by DSS.

The database subsystem component contains the following i) real-time experimental data which should represent the complete range of operating conditions including all possible fault occurrences of the centrifugal pumping system, ii) data of Hazard and operability study (HAZOP) and iii) data of failure mode and effect analysis. The knowledge base subsystem component contains the information about the construction, working principle, procedure and performance characteristics of centrifugal pumping system, detailed theoretical information about the safety management tools such as HAZOP & FMEA and concept, applications & potential safety gains of DSS implementation. The dialogue base subsystem component contains the set of possible question for user interaction. The user can clarify the queries via the user interface developed with various categories of queries which is also incorporated.

Thus a safety personnel/any operating personnel can use the developed DSS for diagnosis as well as the theoretical concepts needed. It also delivers domain-specific expertise to people who are not specialists and who therefore might not avoid those hazards without interactive guidance. It places greater emphasis on rapid and timely support of skilled or semiskilled operators at the time of decision making.

5. CONCLUSION

This paper has presented the development of decision support system for safety management of rotary system. The rotary system considered for this study is centrifugal pumping system. The developed decision support system consists four subsystem components namely model base, knowledgebase, database and user interface. The model base contains a neural network based fault detection model and fuzzy logic based fault diagnosis model of centrifugal pumping system. The data required for the development of model have been obtained through the real time simulation of the system considered. Totally 7 category of faults from the centrifugal pumping system were considered in the developed model. For the ANN Model the testing data are fed to the designed model to check the accuracy. The testing samples are different from the training samples and they are new to the trained network. Simulation results show that this neural network approach is very much effective in detecting the various faults in the system. In the fuzzy logic based fault diagnosis model, the fault-symptom relationships were expressed in the form of fuzzy if-then rules. The real time numerical data collected from the system are used to fine-tune the membership functions and the fuzzy rule base. Simulation results from the model produced accurate results. The effectiveness of the proposed model has been demonstrated through different fault detection in the centrifugal pumping system. Further work includes the implementation of the system with the adaptive approach and the consideration of the diagnosis of unexpected faults in a generalized approach for industrial applications.

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