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Design of a fault detection expert system to diagnose errors in the Polypropylene production process

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Abstract

Expert systems are computer tools that, like an expert, advice on issues related to their area of expertise and support decision-making when required. These systems can be defined as counseling programs to solve complex problems that require experts to be solved. In this research, an expert system was designed to detect faults in the chemical process of polypropylene production. Using this system, all the information and experiences of experts can be accessed and used as a comprehensive resource. First, a diagnostic classification and fault detection is provided, which is prepared from a review of the literature related to the design of expert systems as well as the knowledge available in the polypropylene production process. Also, in this stage, the feasibility of the project was investigated, which was done by holding meetings with experts. In the second stage, the groups and constituent elements of the classification are explained. Likewise, more than 300 system faults were identified and coded to acquire the required knowledge for the system. In the next stage, the main elements of the fault detection system in the polypropylene production process are classified. Information related to Marun Petrochemical Company was used as a case study to further investigate the designed system. Also, the main reasons for defects and faults of the process were investigated and the frequency and percentage of each were calculated and reported. After classifying the reasons for the stoppages, the faults leading to each stoppage were extracted and classified. In the design stage, the prototype was coded for the system using JavaScript programming language and nodeje technology. In order to design the algorithm, each of the faults with one of the causes was considered as a scenario and related to a unique question to act as an intermediary between the expert system and the user in designing the user interface. Factors affecting the evaluation include the cost-consuming nature of the solution, the time-consuming nature of the solution, and the frequency of iteration of the fault. Finally, in the testing stage, the proper performance of the designed expert system was ensured.

Keywords; Fault detection, expert system, diagnose errors, Polypropylene production process

1- Introduction

In Marun Petrochemical Company, all types of polypropylene grades are produced from propylene and ethylene monomers with Basel's Spheripol technology in two bulk loop reactors (BLR) and one gas phase reactor (GPR).

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Propylene (and in copolymer grades of propylene and ethylene) as the main feed of the unit, in loop reactors, enters the polymerization reaction with the intervention of catalysts and co-catalysts and reacts about 60% of the input feed and polypropylene polymer is produced (Stankiewicz et al., 2000). In the next step, the resulting slurry - which is a combination of unreacted polymer powder and monomer - is transferred to the isolation and recovery area for isolation and recovery of the monomer. In this area, the monomers are separated from polypropylene and returned to the feed tank for reuse (Stankiewicz et al., 2000). In the polymer processing area, in the steamer system, the resulting powder is first exposed to steam; as a result, the hydrocarbons evaporate and separate, and also, the catalyst and co-catalysts are neutralized. The powder, which has been humidified by evaporation, is then dried in a dryer system with hot nitrogen. Finally, the processed polypropylene, which is the output of this area, is sent to powder silos for storage (Stankiewicz et al., 2000). The next area in the production cycle is the extruder and pelletizing. The powder resulting from the process is prone to degrading when exposed to air and oxygen and is not suitable for use in downstream industries. To prevent degradation, in the pelletizing area, the polypropylene powder is mixed with stabilizers and anti-oxidants (and based on the use in specialized downstream additives) and after melting by the extruder, it is converted into granules. These granules are packaged and marketed after pelletizing and passing quality tests.

In the production process of this strategic product, there are many problems that not only damage the quality of the product and customer satisfaction, but also affect the environment by increasing industrial waste. Also, the occurrence of problems in the production process increases repairs, unintentional stoppage of the unit and burnout manpower, and the cost of production. In most cases, the decline in product quality, unintentional stoppage of production units or production of the waste are due to hidden faults caused by previous activities of the process. In other words, the faults observed in the final product, each stage of the process or equipment may have originated from the previous stages (Marun propylene unit). Therefore, among the factors that cause process faults are the following:

- Main process factors (improper catalyst preparation activity, improper control of process conditions in the reactors, improper management of polypropylene powder transfer to extruder, improper control of extruder conditions and product pelletizing, human error, defects in monomer recovery process, improper processing of the produced polymer powder.
- Poor quality of the final product of utility factors (poor quality of feed, poor quality of additives, cutting off facilities (including electricity, steam, cooling water, instrument air, demineralization (DM) water and nitrogen)
- Maintenance factors (breakdown and failure of electrical equipment, breakdown and failure of electronic equipment of instrumentation, mechanical breakdown of equipment, insufficient accuracy of the maintenance team during repair, use of spare parts of poor quality)
- Software factors (emergency shutdown system (ESDS) errors, distributed control system (DCS) errors)

Product quality and production stability and reduction of waste and costs depend on various variables. Each of these variables, in turn, have a significant effect on the output of the process, which makes it difficult to resolve the fault in the status of occurring the fault in the production process. Fault diagnosis (FD) for the production process is usually done by experts. These people use the knowledge and experience they have gained over the years - in hundreds of situations - to solve problems. The number of experts is limited and it is expensive to use their experience and knowledge in their field of expertise, in addition, they may not be available when the organization needs those (Durkin et al., 1998). Experience and knowledge of experts, knowledge contained in the documents provided by the unit designer, as well as written data and process conditions of the unit that have been recorded during 14 years of operation can be collected and stored in a database. This database leads to the development of expert computer systems that are able to diagnose faults of the polypropylene production process. To design an expert system, we will analyze problems and faults in three dimensions or general levels, including faults and issues related to support activities, faults and issues related to main process activities, and faults and issues related to process control activities. When the system is out of normal and designed activity, diagnosis of system defects can help detect abnormal events, reduce system loss and prevents system shut-down. Therefore, FD is an important and significant issue for industrial interns and scientific researchers (Tahmasebi et al., 2007).

Analytical methods of artificial intelligence and statistical methods can be used for the FD process. From the modeling perspective, there are methods that need precise process models, semi-quantitative models or qualitative models. On the other hand, there are methods that do not consider any form of model information and rely only on data from previous processes (Chen et al., 2012). Furthermore, having process information, there are difficult techniques for fault searching that can be used to FDs. The FD methods discussed can be divided into two categories, data-driven methods and process model-based methods. An expert uses both of the above techniques simultaneously and in combination to diagnose the system faults and provide a solution to solve the fault.

An expert system is a system that mimics and simulates the inference process and expert knowledge in identifying and solving problems in a specialized field (Zuluaga et al., 2015). In other words, expert systems are computer tools that, like an expert, advice on issues related to their field of expertise and support decision-making if necessary, these systems can be defined as counseling programs to solve complex problems that require experts to be solved. Therefore, the purpose of these systems is to copy the skills of one or more experts and problem solving is the responsibility of the expert. According to Edward Feigenbaumm, an expert is a computer program that can recommend, classify, communicate, advise, design, identify, explain, search, predict, interpret, justify, learn, manage, supervise, project, display, review, plan, train, and help experts solve problems.

The main objective of this research is to design a model for a fault diagnosis expert system (FDES). Since the working method is a combined method and we will not use only statistical methods, we do not have a statistical hypothesis. The research questions are also detailed in the previous section. The fundamental non-statistical hypothesis in creating FDESs is that FDES have the ability to replace expert human in the production process. Performance monitoring and FD in the process have received a great deal of attention in recent years. Researchers have shown that system performance control can be improved by implementing various techniques, including artificial intelligence (Khorasgani et al., 2015). This development means that with these techniques, a processing plant will be capable of producing more products using a safe, reliable and cost-effective control system. The idea behind performance monitoring and error diagnosis is able to identify process control weaknesses and radically correct control system problems with minimal delay. These control problems will have consequences such as insecurity, instability, poor product quality, higher energy consumption and loss of opportunity and time (Xiong et al., 2010).

This project and the expert system designed in it, firstly, makes the knowledge in the process environment, especially the tacit knowledge of experts in the industry, which is scattered, to be collected, categorized and compiled. The knowledge engineering used to build a knowledge base will turn the scattered and sometimes unrelated sources of knowledge and experience of experts into a coherent, uniform, reliable and valuable resource. Second, by creating an expert system, access to information, knowledge and experience of experts, even when they are not in the workplace, is facilitated. Third, by facilitating the identification of faults and speeding up the finding of solutions to solve them, it will significantly contribute to the sustainability of production, reduced waste, reduced material and energy losses, reduced number and time of equipment repair and, consequently, reduced production costs and product prime costs. All these factors will lead to the optimal use of resources, stability of product quality, customer satisfaction, strengthening of the product brand in the market and thus increase in the company's profitability, strengthen the importance of the project and the need for its implementation.

In this paper, first, a fault detection and diagnostic classification is provided, which is prepared from a review of the literature related to the design of expert systems as well as the knowledge available in the polypropylene production process by Spheripol technology. In the second stage, the groups and constituent elements of the classification are described. In the next stage, the main elements of the (FDS) in the polypropylene production process identified in this research based on classification are discussed with an example. Finally, integration of augmented reality, which could be used as a potential new strategy, is discussed to further help in the FD.

2- Literature review

In this section, the research literature on expert systems and identification of errors in chemical processes such as the polypropylene production process is reviewed. İpek et al. (2013) designed an expert system based on the material selection approach for the manufacturing process. They tried to solve the materials selection problem by means of an expert system approach to manufacturing. According to this method either four or five different properties are inspected for each automotive part such as impact resistance, lightness, formability, low prices, and vibration. Accordingly, polymetric and polymetric methacrylate materials were selected for the bumpers. Fiberglass plastic and carbon fiber plastic were also selected for high-speed driving. Iron and steel were also considered for low speeds.

Deb et al. (2013) considered a method for integrating usage analysis in an expert system for design evaluation. They designed a technique that allows designers to enter their opinions about uncertainties and assumptions about users' perspectives into the system. The general approach is to eliminate perspectives of innovative roles that directly include assumptions about users and replacing them with the user-friendly multi-perspective possible use and probability distribution functions. Ali and Saudi (2014) provided research on an expert system for diagnosing and managing oral problems. They received a system on a CD-ROM and evaluated it for use with a printed questionnaire. Oral conditions integrated into the database included various diseases. Their results showed that the average total score of program quality was 3 with 75% success rate. It can be concluded that the support system introduced to students has been helpful in diagnosing and treating most diseases

Kumar et al. (2016) provided a study on the framework of big data MapReduce to identify errors in mass-based production. They used the MapReduce framework to identify automated patterns based on error diagnosis that could be solved through an unbalanced data problem in a large production. Their framework uses a hybrid approach to dealing with big data for smart decisions. They also compared the classification performance of machine support vectors by standard techniques and provided the results. Tan et al. (2016) analyzed the use of expert systems. To investigate their research, a review of the research and applications was provided. They classified the support system and its applications as diagnosis, maintenance, training, prediction, design and planning and monitoring, selection, and detection.

Marie et al. (2018) in their research investigated the knowledge management system to mitigate supply chain risk with uncertainty. They also used an automotive battery supply chain to analyze their proposed method. In their paper, the process of designing a knowledge management system is described to mitigate risk. Their method began with determining the knowledge needed to solve uncertainty problems and analyze system requirements. The results of their study show that the field of knowledge that needs to be managed should ensure the sustainability of the process and lead to a mitigation of waste and losses.

Daemisch (2018) provided the constraints of the algorithms used in the support expert system and investigated its shortcomings. They also provided examples of why support systems are being replaced by final perspective and evaluation of experimental results through human support. Complex facts are not automatically covered when such costly and important decisions have to be made. The author also provided another comprehensive study on the comparison of support systems and human support.

Faure et al. (2020) addressed fault detection and diagnosis for large solar thermal system. Accordingly, an overview of fault types and compatible methods was provided. Their research affects solar thermal systems and current approaches to detect and identify faults. Tammaro et al. (2020) provided a microfluidic platform for the design of acidic nanoparticles and for diagnostic applications. They proposed a hydrodynamic flow concentration approach for the production of acidic particles. The results of their research showed that multi-method nanoparticles can be used as MRI imaging. Smerichevskyi et al. (2021) provided the practical use of diagnostic symbols of the enterprise export-import activity in the disruption conditions of world economy sustainable development. Their goal was to solve an important scientific problem for further development of the basis of managerial decisions in the implementation of export and import activities.

In a paper, Tan et al. (2016) review the applications of expert systems and classify the application of these systems into 15 groups: FD, maintenance, an instruction for users, interpretation, prediction, prediction of trends, design and planning, monitoring, control, monitoring control, classification, exploration, debugging, and selection. They also provide examples for each of the application areas. According to them, the use of expert systems in the field of FD has a greater share than other fields. So far, no report or paper has been reported on the FD of chemical processes in petrochemicals in the field of polypropylene production process. Several research works inside and outside the country have only designed a model for using the expert system in FD on special equipment (such as turbines in refineries) or small processes (such as measuring the industrial effluent characteristics of oil industries). No research has been observed in the field of petrochemical industries, especially FD in the production process (Venkat et al., 2003; Hoskins et al., 1998; Hohne et al., 1989; White et al., 1999; Stephanopoulos et al., 1996; Bahrami et al., 2013; Azar et al., 2016).

The contribution of this is the novelty in the field, scope, and actual implementation in the petrochemical industry. The methodology for a detailed knowledge base modeling is also innovative. The knowledge base of the project was created by combining the knowledge of experts, documents and parameters of unit design, as well as the existing data and system performance trends in the recent years.

3- Methodology

3-1- Systems based on process history and model-based FD

The development of FDDS includes not only various areas of knowledge but also a variety of methods. In the proposed classification, the group related to the techniques used for FD and detection is described as the second group. This group is related to the development of error detection system using a suitable technique and the use of special knowledge. A brief explanation is given below each element. The first element in this group is an analytical approach. Because two common mechanisms for this method, parameter estimation and fault detection monitors are used to develop the system. This approach was developed based on a quantitative model in a classification accepted by Venkat et al. (2013) for the Aluminum industry (Chen et al., 2012). Figure 1 shows the main steps of model-based fault diagnosis.

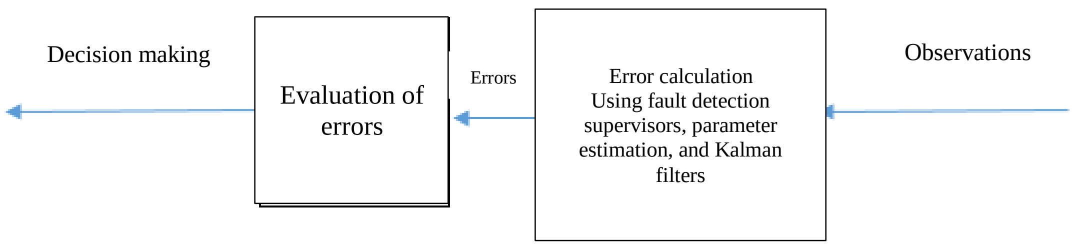

Fig 1. Two main steps of model-based fault detection

In an error diagnosis system (EDS) for the aluminum production process, an extended Kalman filter was used to not only estimate the concentration of alumina in different parts of the aluminum reducing cell, but also to show the abnormal distribution of alumina. A mathematical model was developed to estimate the alumina concentration. The error was generated from the difference in the expected alumina concentration by the system model and the actual concentration (Zubair, 2020). Abnormal alumina distribution was diagnosed when the error was significant.

Due to the complexity of the polymerization process in production line reactors and the multiplicity and variety of machines, this method requires complex models that are practically expensive and unusable for petrochemical processes. An expert system, which is a process history-based approach, is the second element in this group. In a process history-based approach, prior knowledge is extracted from large amounts of historical data. As shown in figure 2, knowledge extraction from this data can be divided into qualitative and quantitative methods (Md Nor et al., 2021). A well-known example of a qualitative method is the expert system, in which prior knowledge is obtained from specialists and the knowledge and experience of human resources in a specific field is collected. This knowledge is used in FD to conclude an out-of-control situation by combining user facts and the knowledge of human experts gathered in knowledge databases. In the polypropylene production process, knowledge related to the diagnosis and correction of operational faults is collected in two formats: interviews with experts and specialists, as well as referring to the collected written sources of the production line manufacturers. Therefore, there are two subsystems in this section. The former includes the knowledge and experience of specialists and experts in the petrochemical industry and polypropylene production process and the latter includes special knowledge that is available by the designers and manufacturers of this unit as start-up documents and a guide to production operations (Thomopoulos et al., 2016).

Neural networks is the third element in this group, which is also a process history-based approach. As shown in figure 2, the quantitative method can be divided into statistical and non-statistical methods. The use of artificial neural networks is a non-statistical approach used in FD to detect the pattern of data received using nonlinear mapping between input (data patterns) and output (error classes). This mapping involves hidden neurons that are highly interconnected and arranged in layers. Artificial neural network was used by the Polymer Research Institute to predict the physical and mechanical properties of polypropylene in the same process. In this project, the 6-month history of process conditions was used as input (data patterns) to train networks. The created network is capable of predicting the final properties for homopolymer grades with high accuracy. However, the use of neural networks does not have the ability to generalize/explain the behavior and therefore the use of these networks is not suitable for fault detection (Tan et al., 2016).

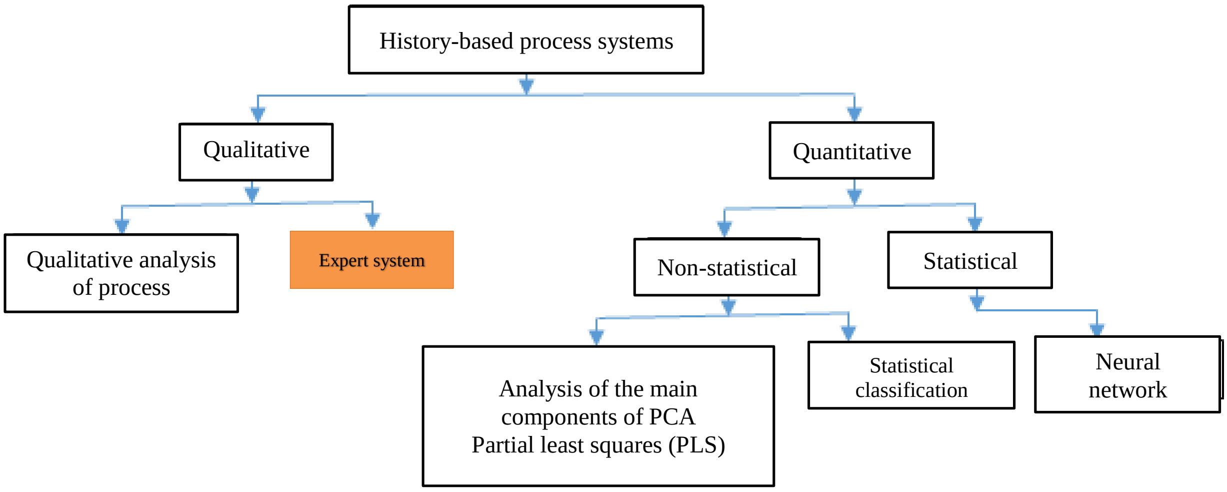

Fig 2. Classification of history-based process systems

The fourth element in this group is the use of multivariate statistical methods, which is also a quantitative and process history-based approach. Multivariate statistical techniques such as Principle Component Analysis (PCA) and Partial Least Squares (PLS) are used to extract a number of latent variables from ordinary operational data retrieved from historical databases to form an experimental model (Zhang et al., 2005). Therefore, in the future, whenever the performance behavior of the production line differs from the experimental model of the natural process, unexpected changes and faults in the process can be diagnosed (Klyuchko et al., 2018). Multivariate statistical techniques such as PCA and PLS require an online connection to the control system to monitor the process and issue a warning when a fault occurs. Since the control system is completely isolated from other networks in the organization to maximize safety in petrochemical processes such as polypropylene production due to the high cost of the process and the destructive effects of malware or viruses penetrating the control system. It is not possible to create an online gateway for data exchange between the distributed control system (DCS) and the decision support system (DSS). Therefore, multivariate statistical technique cannot be used in this project.

Presentation of the results: The third group in this classification describes three modes of presenting the identification results: text, graphic (visual) and three-dimensional (3D). Providing the diagnosis results to the operator can be more instructive if the operator's needs are considered in terms of a clear visual representation in the page design (Goodarz et al., 2007). This theory is supported by research conducted by Harris et al., which includes color and statistical diagrams in the design of a monitoring control system. The use of dark and light contrasting colors in this system clearly shows the warning time for the department leader in a smelting plant to act accordingly. In addition, the color sensitivity of the potential operator should be considered by selecting color palettes that provide effective contrast for all potential visual levels of the color.

3-2- Fault detection expert system in the production process

FD and fault detection knowledge, first element of this system is the discovery of new knowledge based on the relationship created between faults extracted from the history of the production line and the cause of their occurrence. As mentioned earlier, in addition to extracting knowledge from expert interviews, abnormal conditions were identified using data recorded in the production line history and solutions are extracted by reviewing the documents provided by the process builder, and finally they were saved in a knowledge base with a structure of fault/cause/solution. Creating a knowledge base is one of the practical ways to discover new knowledge about FD (Mahmoodi et al., 2015). Since the polypropylene production process is complex, it may be impractical to provide an accurate mathematical model of the process for this purpose due to the difficulty of effective monitoring on the process. Therefore, model-based methods, both quantitatively and qualitatively, have not been considered in this work. On the other hand, there is an increase in the interest in using process history-based approaches to FD in industrial applications (Md. Nor et al., 2020). Davis et al. (2004) state three main reasons for the increased interest as follows: (1) they are easy to implement. (2) Little effort is required for modeling. (3) Little prior knowledge is required.

A number of FD techniques based on the process history, including expert systems and neural networks, can be used for the polypropylene production process. Expert system design based on "backward chaining" is more appropriate for FD. Because of the complexity of the polypropylene production process, it is often difficult to find abnormal performance patterns. Engineers interpret the process of the abnormal pattern or the fault based on its history and by adding their reasoning to the knowledge base, they actually open the way for the operator to make decisions in the event of an abnormal situation. By searching a computer system that is connected to a bank of information and experiences of experts, it will find the fault in the shortest time, identify the cause, and achieve a relatively experienced solution to the problem. Furthermore, by using the possibility of sending feedback, operators can contribute to the creation of an up-to-date knowledge-based diagnosis system (DS) for a complex and large process. However, an efficient expert system requires comprehensive, accurate, and massive data.

As mentioned in the previous sections, the proposed expert system model consists of four main parts (Zubair, 2020):

Knowledge Base: It is a place where expert knowledge is stored in a coded and comprehensible way for the system. The knowledge obtained from data analysis of the last 5 years and interviews with experts are organized in a database with a problem-question-solution structure in the knowledge database. Questions are designed for each problem to use them to identify the cause and offer a solution based on the identified knowledge. In general, the extracted knowledge is stored in the knowledge database in the form of conditional expressions or rules.

Inference Engine: Even when we represent the realm of knowledge by rules, an expert still has to determine which rules to use to solve a particular problem. Moreover, the expert must specify to what extent these rules should be applied. In other words, the expert system will need to decide which law to choose in what case and what grade to choose for evaluation.

The inference device is actually the heart of an expert system. A complex system that uses inference rules to find the final answer or judgment. What makes an expert system an expert system is the way in which these rules are processed. The inference device can work in two ways to achieve the answer (Tan et al., 2016):

Development, implementation and evaluation: The third stage of development is where the platform used to build the AR application is selected as a browser or a platform of the device. This development needs to be focused on the usability and performance of the application. In the fourth stage (implementation), possible problems in setting up the application must first be identified before running the application. A clear operational plan must be developed to assist end users or workers in using the new technology. In the fifth stage (evaluation), user satisfaction is evaluated and the benefits of the application are identified. These five stages (need, design, development, implementation, and evaluation) can be used as a guide in developing an AR application for any manufacturing plant, such as a polypropylene plant. Furthermore, the AR module can also be added to the corrective measure guidelines because AR can be used to highlight a dangerous area in the plant. For example, a virtual fire in a power plant may help an operator gain an in-depth understanding of operational methods in the event of an abnormal situation. Therefore, operator behavior can be tested under normal and abnormal conditions to improve operating procedures (Gao et al., 2018). Figure 3 shows the complete real-world design with comprehensive information for four important functions.

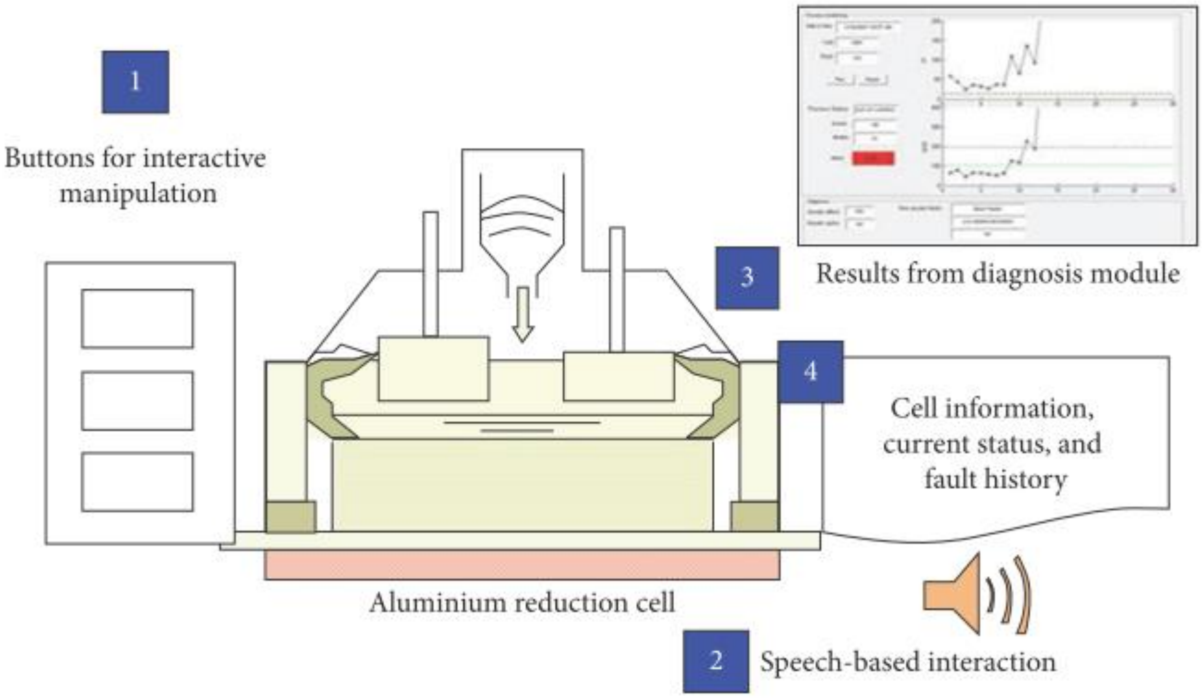

Fig 3. Complete real-world scheme with comprehensive information for four important functions

The development of a fault diagnosis and detection system (FDDS) for the polypropylene production process is a fundamental challenge. This FDDS must be able to accurately show anomalous conditions, although the process is complex and dynamic. In this paper, the proposed classification is described with examples of existing systems. The classification clearly highlights the main elements of FDDS, which include knowledge utilization, FDD techniques, number of uses, and presentation of results. Classification has many applications, including:

(1) To identify the main elements for distinguishing between existing systems;

(2) To identify improved areas for existing systems;

(3) To provide an overview of the system in which various techniques have been used to identify and detect errors.

This classification has helped to develop this work by identifying gaps in existing FDDs and implementing a new approach to creating a new system that is practical, and provides timely diagnosis and detection and is understandable by operators. In the future, the use of Augmented Reality (AR) technology could increase the diagnostic module's competence to diagnose problems in a more practical way. AR can provide an interactive environment, where operators and remote experts can communicate using the same field of view. Since AR can be used to enhance user visibility in an industrial plant, alternative solutions can be provided for design, quality control, monitoring and control, service and maintenance in complex process industries, such as the aluminum smelting industry.

4- Solving the problem and providing the results

An expert system is a system that mimics and simulates the inference process and expert knowledge in identifying and solving problems in a specialized field (Zuluaga et al., 2015). In other words, expert systems are computer tools that, like an expert, advice on issues related to their field of expertise and support decision-making if required, these systems can be defined as counseling programs to solve complex problems that require experts to be solved (Mark, 2010). Therefore, the purpose of these systems is to copy the skills of one or more experts and problem solving is the responsibility of the expert. According to Edward Feigenbaum, an expert is a computer program that can recommend, classify, communicate, advise, design, identify, explain, search, predict, interpret, justify, learn, manage, supervise, project, display, review, plan, train, and help experts solve problems (Durkin et al., 1998). This project will be designed and implemented in the following stages:

Stage 1- Assessment: In this stage, the feasibility of the project was investigated. During the meetings held with the unit process and operation managers, the feasibility of access to information records and process history was assessed. In order to increase the accuracy in the analysis, valid data was identified and categorized. Required knowledge resources such as: records of unit stoppages in the last 5 years, product quality records, control room log sheets, documents and operations guide of the unit designer and builder, experts, and other required reports were specified.

Stage 2- knowledge acquisition: In the knowledge acquisition stage, which is the process of acquiring, categorizing and reviewing knowledge, in the first step, to extract and categorize the system faults, the history of stoppages and their reasons were examined. The faults were coded and recorded in a list entitled "Reasons for Stoppage". Also in this stage, the quality history of products, non-compliant products and the reasons for their production, as well as complaints from customers were categorized. In this stage, a total of more than 300 faults were identified and categorized. Using the backward reasoning technique, the reasons for each fault were extracted and recorded in the mentioned table. From the study of the unit's 5-year history, it appears that different reasons have been recorded for each fault at different times, in other words, each fault may have occurred for different reasons that in order to organize the knowledge base, it was necessary to identify, categorize, and calculate their share in each fault. In this phase, by conducting calculation sessions with experts and in order to determine the dimensions of the problem, the main concepts and methods of problem solving were reviewed by experts and initial tables were prepared. Also, in this stage, documents related to designing the review process model and normal conditions of the system performance were identified, and then the documents of the unit control process, which are recorded in different sections on an hourly and daily basis by the operators or the automatic control system, were reviewed and added to the knowledge base as a solution for fault elimination.

Stage 3- Analysis: In this step, the collected information was analyzed. Knowledge of various aspects of the production process system and knowledge of how it works, manner and the extent of communication between its components, were completed. Then, a basis for the architecture and implementation of a suitable expert system was obtained. The groups and elements that they create for fault detection and diagnostic classification for the polypropylene production process are shown in figure 3. The proposed classification can help determine various factors in creating a FDDS. The groups and elements of this classification are briefly described in the following section.

Fault diagnosis and fault detection knowledge: The first group includes fault diagnosis and fault detection knowledge. The elements of this group represent special knowledge in the polypropylene production process that will be used to develop FDDSs. For this classification, all production line stoppages during 5 years (1394 to 1398)[1] as well as the causes and factors involved in these stoppages were collected and statistically analyzed. Table 1 summarizes this information. The following is a brief description of each element.

[1] 2015 to 2019

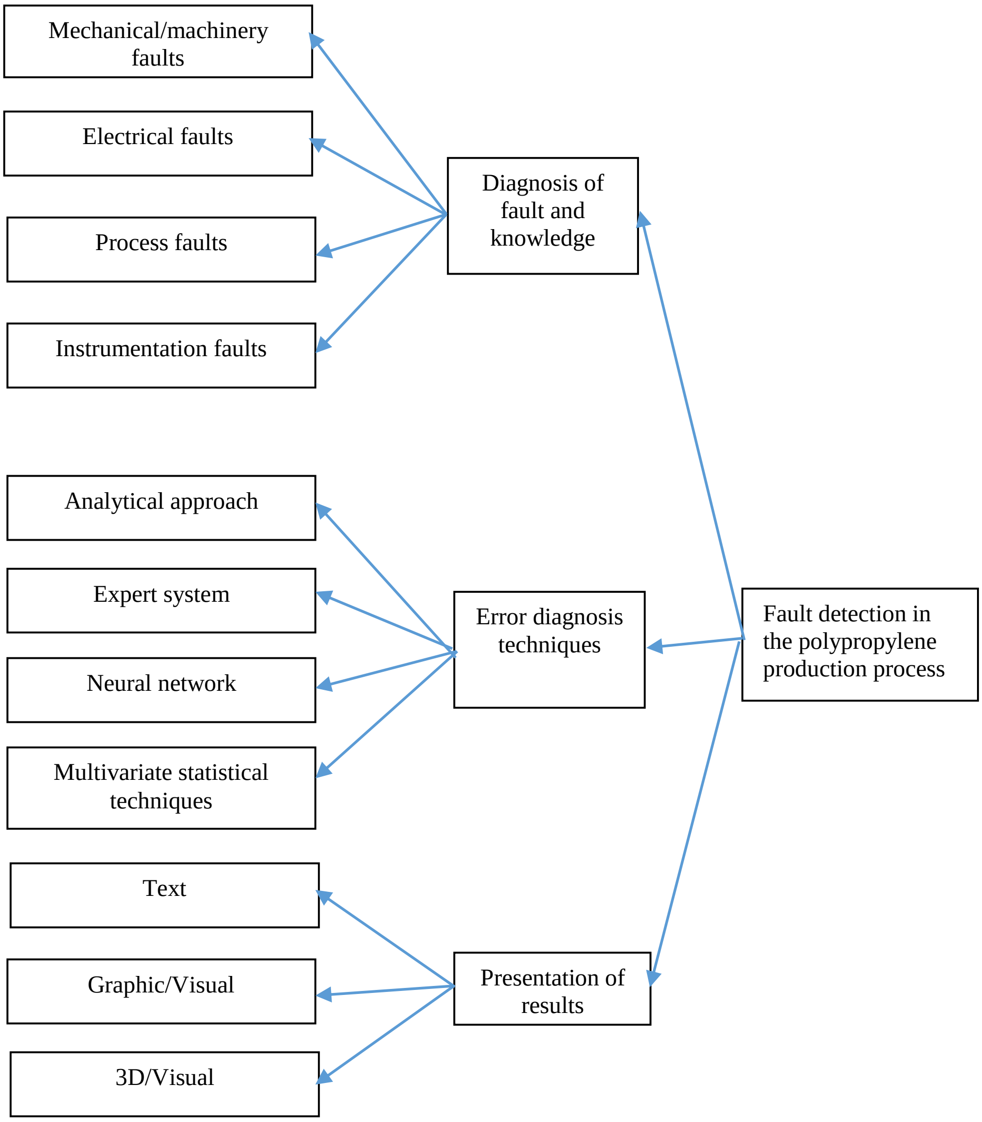

Fig 4. Proposed classification for fault detection in the polypropylene production process

(1) The first element in this group are mechanical or machinery faults. This group includes all mechanical faults of machines that have caused the production line to stop. Mechanical faults are the leading cause of stoppage with 35% of stoppages. **(2)** The second group of causes of production line stoppage is power outages and electrical equipment faults. 29% of stoppages in the last 5 years have been due to electrical faults. **(3)** The third element in this group is process causes. Process causes include all faults that have occurred due to changes in process control parameters and caused the production line to stop. Fluctuations in feed quality to process error of production line operators are included in this element. Process faults are in third place with a 25% share. **(4)** The last group of causes of unit stoppage are instrumentation faults. Instrumentation faults of equipment and control systems are in fourth place with 11% of stoppages.

Table 1. Summary of production line stoppages based on the proposed grouping

Row	Group elements	Stoppage hour	Share of stoppage	Frequency
1	Mechanical/Machinery	936	35%	36
2	Electricity	769	29%	11
3	Process	676	25%	21
4	Instrumentation	280	11%	8
Total stoppages in the years 94 to 98		2661	100%	76

These faults were factors that, in addition to disrupting the production line and depreciating machinery and equipment, caused resources to be wasted due to production of non-compliant products and increased polymer waste. The collected data were classified to design the model. This classification is necessary to help operators form an intelligent knowledge base to develop an expert system as a decision support system when there is no access to experts to prevent the occurrence of disruption in the production with a correct and fast decision.

Table 2. An example of stoppage classification tables

#Sec	Fault	1398		1397		1396		1395		1394		Total		Freq
		Hour	%	Hour	%	Hour	%	Hour	%	Hour	%	Hour	%	
0	Hima Fail		0	128	26%	0	0%	0	0%	0	0%	128	5%	1
0	Power Cut	85	26%	75	15%	203	30%	100	19%	60	9%	523	20%	5
100	Catalyst Line	20	6%	11	2%	40	6%	12	2%	13	2%	96	4%	7
100	P-1001		0%		0%		0%	6	1%		0%	6	0%	1
200	P-2000		0%	10	2%	24	4%	70	14%	13	2%	117	4%	6
200	Sticky Product		0%	49	10%	170	25%	44	9%	60	9%	323	12%	9
200	E-2008 Rubber Joint		0%	15	3%		0%		0%		0%	15	1%	1
200	R-2000	75	23%		0%		0%	123	24%		0%	198	7%	4
200	D-2001	13	4%		0%		0%	24	5%	18	3%	55	2%	3
200	R-2001,2	14	4%		0%		0%	37	7%	180	28%	231	9%	5
300	FT-3001		0%	58	12%	38	6%		0%		0%	96	4%	3
300	T-3001		0%	11	2%	106	16%		0%		0%	117	4%	2
300	DA-3001		0%		0%		0%		0%	75	12%	75	3%	2
500	Lumpy P	65	20%	75	15%		0%		0%		0%	140	5%	3
500	D-5001		0%		0%	32	5%		0%	36	6%	68	3%	3
500	DR-5002		0%		0%	41	6%	66	13%	8	1%	115	4%	6
500	Pif Puf		0%		0%		0%	22	4%		0%	22	1%	1
600	RU-6001		0%		0%	23	3%		0%		0%	23	1%	1
800	Zepplin		0%	4	1%		0%		0%		0%	4	0%	1
800	Extruder	55	17%	46	9%		0%		0%	83	13%	184	7%	6
800	XV-80101		0%	17	3%		0%		0%	24	4%	41	2%	2
800	RV-8000,1,2		0%		0%	6	1%	10	2%	36	6%	52	2%	3
800	B-8001A		0%		0%		0%		0%	32	5%	32	1%	1
Total		327	100%	499	100%	683	100%	514	100%	638	100%	2661	100%	76

The table above shows the reasons for unit stoppages based on iteration and the share of total stoppages. By analyzing and investigating the table above, the most frequent cases that have a greater share in the recorded stoppages were identified and selected for the first phase of the project. Another source of data collected were faults that led to customer complaints about product quality. This information was reviewed over three years and the results were classified according to the table below.

Table 3. Classification of customer complaints

	Major reasons for complaints	Number	Percentage
1396	Packaging	3	37.5
	Wrong product loading	1	12.5
	Jumbo quality (non-compliant)	3	37.5
	Heterogeneous distribution of materials in products (process)	1	12.5
1397	Jumbo quality (non-compliant)	3	30.0
	Error in granulation and product application (process)	1	10.0
	Jumbo quality (non-compliant)	3	30.0
	MFI domain process (process)	1	10.0
	Error in product technical specifications (non-compliant)	1	10.0
	Packaging	1	10.0
1398	Wrong product loading	2	7.7
	Jumbo quality (non-compliant)	3	11.5
	Packaging	16	61.5
	Product quality (process)	2	7.7
	Problems in granulation and product application (process)	3	11.5

After classifying the reasons for the stoppages, the faults leading to each stoppage were extracted and classified. For example, the extruder stoppage was selected as one of the most frequent events to analyze the faults and the analysis result was summarized in the table below.

Table 4. Classification of faults with possible reasons

Detected fault	**Cause extracted from sources**
The granules are fine	Die holes are dirty
The granules are fine	Die temperature is inappropriate
The granules are elongated and pasta-like	Die holes are dirty
The granules are elongated and pasta-like	Die temperature is inappropriate
The granules are malformed.	Die holes are dirty
The granules are malformed.	Die temperature is inappropriate
The granules have a tail.	Shaft cutter is not coaxial with the die
The granules have a tail.	Edges of the blades are not on the same surface enough
The granules have a tail.	Die holes are dirty
The granules have a tail.	Shaft cutter is not coaxial with the die
The granules have a tail.	Corrosion of and damage to the die surface
The granules are stuck together like a rosary.	Die temperature is inappropriate
The granules are stuck together like a rosary.	Shaft cutter is not coaxial with the die
The granules are stuck together like a rosary.	Edges of the blades are not on the same surface enough
The granules are stuck together and clumped.	Corrosion of and damage to the die surface
The granules are stuck together and clumped.	The material and hardness of the blades are inappropriate
The granules are stuck together and clumped.	Shaft cutter is not coaxial with the die
The granules are stuck together and clumped.	Corrosion of and damage to the die surface
The granules are stuck together and clumped.	The cutter set is vibrating

Table 4. Continued

Detected fault	Cause extracted from sources
The granules are stuck together and clumped.	Air pressure is inappropriate.
The granules are stuck together and have a tail.	Corrosion of and damage to the die surface
The granules are stuck together and have a tail.	The cutter set is vibrating
The granules are stuck together and have a tail.	Air pressure is inappropriate.
The granules contain feather-like particles.	Shaft cutter is not coaxial with the die
The granules contain feather-like particles.	Die holes are dirty
The granules contain feather-like particles.	Corrosion of and damage to the die surface
The granules contain feather-like particles.	Die temperature is inappropriate
The granules contain feather-like particles.	The blade has been corroded or damaged
The granules contain feather-like particles.	The cutter set is vibrating
The granules are stuck together in two or three but do not have a tail.	Shaft cutter is not coaxial with the die
The granules are stuck together in two or three but do not have a tail.	Edges of the blades are not on the same surface enough
The granules are stuck together in two or three but do not have a tail.	Die holes are dirty
The granules are stuck together in two or three but do not have a tail.	Corrosion of and damage to the die surface
The granules are stuck together in two or three but do not have a tail.	The blade has been corroded or damaged

As shown in, table 4, the occurred faults often have common causes. Any fault (F) may occur for n reasons (C). So any fault can be represented as the following mathematical function:

$$f(F)=C_n \quad (1)$$

Stage 4- Design: In this phase, the overall structure and organization of system knowledge is created. The appropriate software tool is selected. In this phase, a prototype of the program is created to gain a good understanding of the problem. Conventional programs for designing expert systems, such as Prolog and CLIPS, were not used as they are old. By examining the software based on Expert System shell in the market, such programs were not used due to sanctions and some bugs in domestic software (such as a program developed by Jahad Daneshgahi in 2012. It was decided to code for the system using JavaScript programming language and nodeje technology.

To design the algorithm, in table 4, each of the faults with one of the causes was considered as a scenario and related to a unique question to act as an intermediary between the expert system and the user in designing the user interface. With the answer yes or no to the system question, the user chooses to either continue the query or provide a solution. Table 5 is the completed form of table 4 as follows.

Table 5. Assigning questions to each of the defined scenarios

Identified fault (F)	Cause extracted from sources (C)	User interface question (Q)
The granules are stuck together and clumped.	Shaft cutter is not coaxial with the die	Has the maintenance work been done in the area of the cutter or has the device had a heat shock?
	Edges of the blades are not on the same surface enough	Has the uniformity of the surface of blades not been checked before starting? (rim and face method)
	Corrosion of and damage to the die surface	Has this problem persisted in recent times?
	The material and hardness of the blades are unsuitable	Are the blades broken or corroded enough?
	The cutter set is vibrating	Does the vibration analysis results show vibrations above 100 microns?
	Air pressure is inappropriate.	Is there a drop in pressure or a disturbance in the regulation of forward and backward pressure?

Therefore, the result of the query between the user and the program is a definite yes or no answer. If the answer to question Q_n is yes, the cause of C_n will be identified as the cause of the fault and the solution S_n will be provided. Table 6 is a completed form of table 5. In this table, the causes of the fault are evaluated and arranged in such a way that the fault can be fixed at the lowest cost. Factors affecting this evaluation include the costly nature of solution (C), the time-consuming nature of solution (T), and the frequency of fault iteration (f). Each of the causes as well as the proposed solution was rated by experts from 1 to n (number of causes). Because the higher the frequency of iteration of the fault based on a particular cause, the greater the probability of a fault occurring with that cause, the number assigned to f is inverted. The higher the probability of occurrence, the lower f-score that cause will get. Then, based on the score of each item, the priority of each of the factors in column C is from 1 to n. So that C_n with a lower number takes less n and is in the higher table.

$$P = f \times T \times C \tag{2}$$

Fig 5. Intelligent system of fault detection in the polypropylene production process

Thus, our knowledge base consists of tables, each of which is designed and prioritized for a specific fault in the form of table 6. Fault detection algorithm: For fault detection, the user finds the fault by searching among the recorded faults. This can be done by typing the intended fault or scrolling. After finding the intended fault, the user clicks on Continue. If the fault is new and not in the database, the user can request for it to be recorded by contacting the system administrator and the user.

Table 6. Summary of causes, questions, and solutions of identified faults

Identified fault (F)	Cause extracted from sources (C)	User interface question (Q)	Proposed solution (S)	C	T	f	P
The granules are stuck together and clumped.	Shaft cutter is not coaxial with the die C_4	Has the maintenance work been done in the area of the cutter or has the device had a heat shock? Q_4	check the coaxiality maximum error 0.05 mm and target error 0.02 mm S_4	4	4	3	48
	Edges of the blades are not on the same surface enough C_2	Has the uniformity of the surface of blades not been checked before starting? (rim and face method) Q_2	Make the surface of the blades coaxial. Maximum up and down 0.03 and target 0.02 mm S_2	3	3	2	18
	Corrosion of and damage to the die surface C_6	Has this problem persisted in recent times? Q_6	Change the die plate S_6	6	6	5	180
	The material and hardness of the blades are unsuitable C_6	Are the blades broken or corroded enough? Q_5	Change the blades S_5	5	5	4	100
	The cutter set is vibrating C_3	Does the vibration analysis results show vibrations above 100 microns? Q_3	Check the vibrations. Maximum 100 and target 50 microns S_3	2	2	6	24
	Air pressure is inappropriate. C_1	Is there a drop in pressure or a disturbance in the regulation of forward and backward pressure? Q_1	Check and adjust the forward and backward pressure. S_1	1	1	1	1

After selecting the fault, Q_n is asked in the order of priority described earlier. The program continues to ask and answer questions until it receives a yes answer from the user. In each row that ends in a yes answer, the cause of the fault is identified and the solution is shown to the user as the final solution. If none of the questions end in a yes answer, the program has no answer and asks the user to record the process conditions and their opinion to upgrade the program.

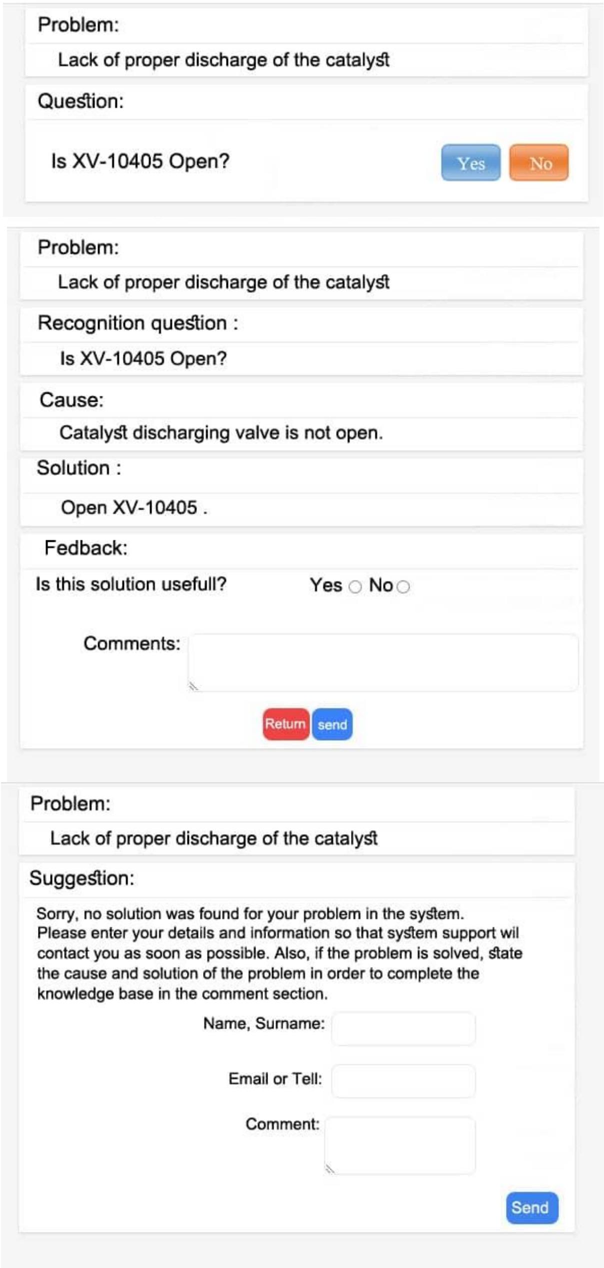

Fig 6. Detected problems and suggestions

In short, the fault detection process occurs as follows:

1. The user searches among the problems in the system and selects the desired problem.
2. A set of CQSs related to the problem is formed.
3. If there is anything left in the CQS set that is not asked of the user, it goes to the next step. Otherwise it is transferred to Step 6.
4. A CQS is selected and the relevant question is displayed to the user. If the user chooses to answer yes, it will go to the next step. If the user selects no, the CQS related to the question will be removed from the set and it will return to the previous step.
5. The cause and solution related to the selected CQS is displayed to the user and information about the process as well as the user feedback are recorded. It is transferred to Step 7.
6. The user is informed that there is no solution to the problem in the knowledge base. The user suggestion/feedback is recorded and transferred to Step 7.
7. The information entered by the user and the results are stored in the database in the form of feedback.
8. We return to Step 1.

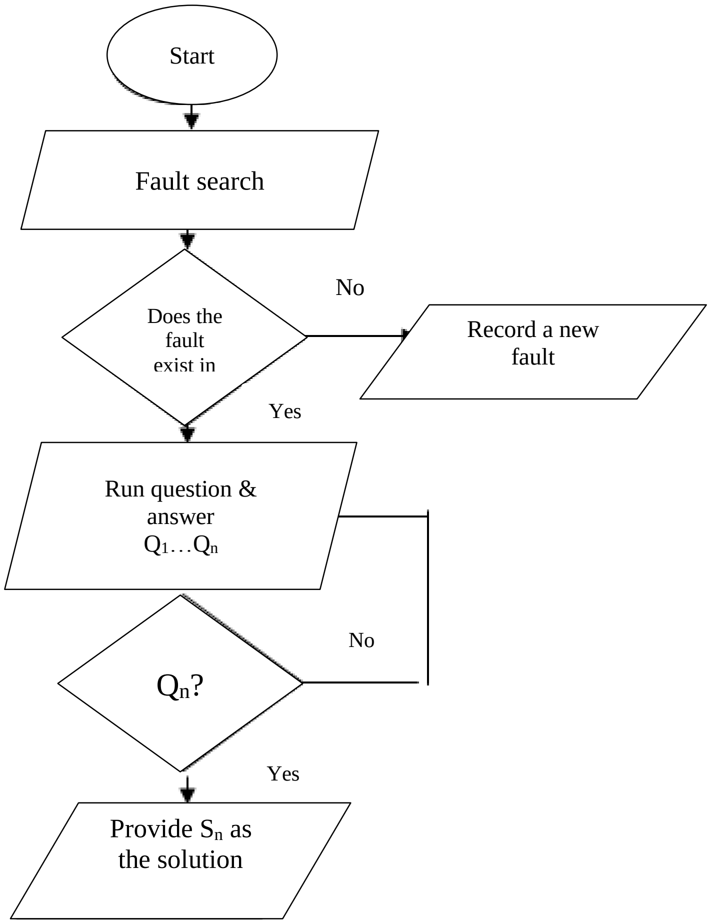

Fig 7. Fault detection algorithm and suggestions provided

Stage 6- Test run: The purpose of this stage is to ensure the proper performance of the designed expert system (in various situations that may be encountered during the use of the system). In other words, the goal is to find possible system errors for its proper, correct, and optimal performance during its use. The designed system must be able to operate in different situations in a more desirable and acceptable way (both in terms of performance and in terms of user comfort). The program was uploaded and tested for easy access and execution on a server at http://expert.agileapp.ir/.

A- Login page:

The system administrator can define the access level for different users by defining them.

Fig 8. Login page of Marun Petrochemical System

B- Program modules:

- ✓ User Management: Introducing and determining the level of user access
- ✓ Rules for file upload: This knowledge base is updated using this module. Rolls and information are processed and prepared in an Excel file and placed in the program through this module. This section has been developed as one of the most innovative parts of the software so that only by analyzing and preparing the file according to the conditions of each process unit, this software can be used. No need to manipulate the coding to update the information.

Fig 9. Uploading the file in the intelligent system of polypropylene production process

- ✓ Knowledge base: By selecting this option, the user can access all tables of the knowledge base seamlessly. This section can be used for training programs or updating the system by experts.

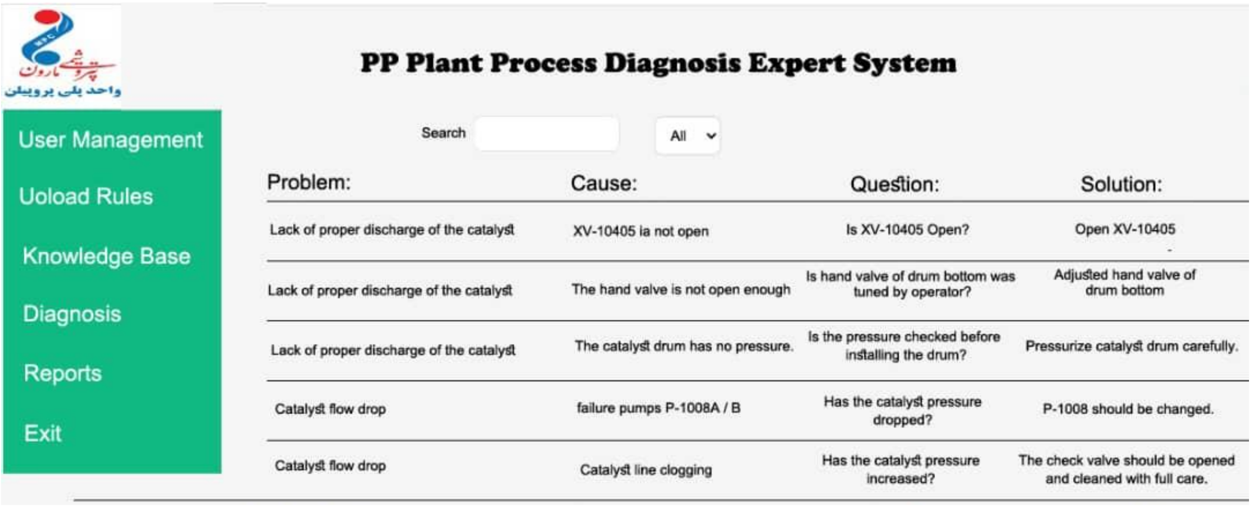

Fig 10. Search for problems in the polypropylene production process

- ✓ Fault detection: It was previously described as the main module.
- ✓ Report: A comprehensive report on the usage history of users can be provided in this section. The percentage of usefulness or non-usefulness of tips in the program is recorded based on user feedback in this section. The report will be available by selecting the time period.
- ✓ Exit

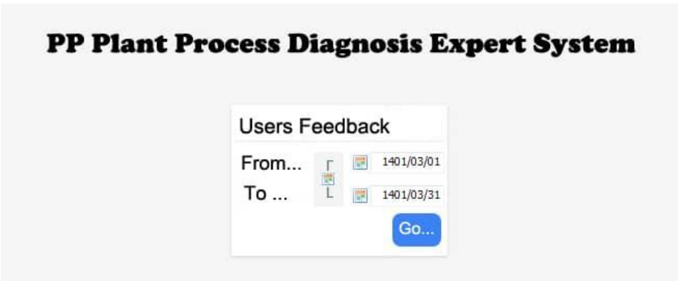

Fig 11. Reporting on user feedback

The main entities of the provided system are as follows:
1) User: is responsible for authenticating and maintaining user information.
2) Problem: It indicates a fault/defect/problem in the production process. Each problem includes a number of CQSs that are useful to fix it.
3) Triple combination {CQS: Question, Cause, Solution}: This triple combination represents the solution to the problem.
Question: A question that must be asked of the user in order to identify the solution. The answer to the question will always be yes/no.
Cause: The cause of the problem is explained to the user so that the user has a better view of the process.
Solution: The instruction that the user must execute on the production line to solve the problem.
4) Feedback: Information received from the user at the end of the fault detection process to improve the knowledge base and system performance in the future. This information can be seen in the user feedback report and includes the following information:

User profile: The identity information of the user who is logged in the system.
Feedback result: Has the user answered at least one of the CQS set questions in the affirmative?
User feedback on the solution: If the CQS option is positive, the user view on the effectiveness of the solution provided

5) User suggestion for solving the problem: If the CQS option is negative, user suggestion for solving the problem

5- Conclusion

In this research, an expert system was designed for fault detection in the chemical process of polypropylene production. Using this designed system, all information, knowledge, and experiences of specialists and other experts can be accessed and can be used as a comprehensive resource. In this system, by identifying faults and speeding up finding solutions, it will have a significant effect on reducing waste, material and energy losses, reducing the number and time of equipment repair, and reducing production costs and the prime cost of the product. For this purpose, first, a diagnostic classification and fault detection is presented, which is prepared from a review of the literature related to the design of expert systems as well as the knowledge available in the polypropylene production process. Also, in this stage, the feasibility of the project was investigated, which was done by holding meetings with experts. In the second stage, the groups and constituent elements of the classification are explained. Likewise, more than 300 system faults were identified and coded to acquire the required knowledge for the system and a list of reasons for the stoppages was designed.

In the next stage, the main elements of the fault detection system in the polypropylene production process are specified based on classification in this study. Finally, the integration of augmented reality, which could be used as a potential new strategy, is discussed to further help in diagnosis. To further investigate the designed system, information related to Marun Petrochemical Company was used as a case study. The identified faults were classified and analyzed in the groups of mechanical or machinery faults, electrical faults, process faults, instrumentation faults. Also, the major reasons for defects and faults of the process were investigated and the frequency and percentage of each were calculated and reported. It was observed that most of the major reasons for complaints in the year 1398 (2019) were related to packaging and then to the jumbo quality (non-compliant). After classifying the reasons for the stoppages, the faults leading to each stoppage were extracted and classified. For example, the extruder stoppage was selected as one of the most frequent events to analyze the faults. In the design stage, a prototype of the program is created to gain a good understanding of the problem. For this reason, it was coded for the system using the JavaScript programming language and nodeje technology. To design the algorithm, each of the faults with one of the causes was considered as a scenario and related to a unique question to act as an intermediary between the expert system and the user in designing the user interface. Factors affecting the evaluation include the cost-consuming nature of the solution, the time-consuming nature of the solution, and the frequency of iteration of the fault. Finally, in the testing stage, the proper performance of the designed expert system was ensured. Accordingly, the program was uploaded and tested for easy access and execution on a server at http://expert.agileapp.ir/, and its validation was guaranteed.

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