Journal of Industrial and Systems Engineering
Vol. 12, No. 2, pp. 199-222
Spring (April) 2019

A fuzzy expert system for controlling safety and shutoff valves in gas pressure reduction stations under uncertain conditions

R. Nourian [1], Seyed Meysam Mousavi [2*], Sadigh Raissi [1], Majid Nojavan [1]
[1] *Department of Industrial Engineering, South Tehran Branch, Islamic Azad University, Tehran, Iran*
[2] *Department of Industrial Engineering, Shahed University, Tehran, Iran*
st_r_nourian@azad.ac.ir, sm.mousavi@shahed.ac.ir, raissi@azad.ac.ir, mnojavan@azad.ac.ir

Abstract

Given the increasing use of gas energy and the dependence of large segments of industries and domestic, commercial, and administrative customers on gas energy, the need for sustained monitoring and the avoidance of any interruptions in the provision of gas services is essential and inevitable. One of the vital parts of the gas industry is gas pressure reduction stations, namely CGSs. In this research, a new fuzzy expert system is designed to troubleshoot and control safety and shutoff valves, which are regarded as main elements in controls of the safety of stations. In the presented expert system, the knowledge about the control of the safety and shutoff valves has been obtained from experts and has been entered in a knowledge-base as "if ... then ... else", and CLIPS language has been used for the system implementation. In this system, 164 rules have been utilized. The expert system is designed to be able to make deductions in both certain and uncertain conditions. Decision trees and control flowcharts have been applied in certain conditions. Fuzzy logic and certainty factors have been employed to implement uncertainty conditions in a case study. Concerning the importance of appropriate control of the safety and shutoff valves, increased responsiveness, increased reliability, increased availability, reduced accidents, reduced costs, reduced natural gas loss, and improved safety of the CGSs are expected by the implementation of the fuzzy expert system.

Keywords: Expert systems, knowledge-base, gas pressure reduction stations, fuzzy logic, safety valves, shutoff valves

1- Introduction

Today's growing population and high demand for energy have led to the daily transfer of a large number of energy carriers to residential and industrial centers. One of the types of fuels in the energy market that is used extensively and has less pollution than other fossil fuels is natural gas (Gholizad et al., 2017). Natural gas is applied as a feed-in petrochemical industry to produce products such as chemical fertilizers, polymer materials, and detergents. Furthermore, it is employed in power plants for power generation (Krichene, 2002). Natural gas is extracted from areas that are too far from the places of consumption, and it is necessary to transfer gas to very long pipelines with appropriate pressure. There are some stations near the locations of consumption called gas pressure reduction stations (i.e. CGSs) to adjust the quality and the conditions of the gas in the pipelines to conditions of the gas that is a requirement for consumers (Poživil, 2004).

*Corresponding author
ISSN: 1735-8272,

Iran is the world's first holder of gas with 34 trillion cubic meters of gas and after the United States and Russia is in the third place with an annual production of more than 200 billion cubic meters, and by consuming more than 180 billion cubic meters is the third largest natural gas consumer in the world. Referred to 70% of the country's energy basket that is dependent on natural gas, and subscribers, including domestic, commercial, educational and administrative customers of more than 20 million are often dependent on the flow of gas; if there is any interruption in flow stability, there will be no gas for heating or second fuel storage; and on the other hand, many parts of large industries such as power plants, petrochemical plants, cement, steel, and other dispersed industries of brick, gypsum, and tile factories, as well as industrial towns as main gas consumers are normal (Safarian et al., 2013).

The essential facilities in the consumption's area are the cities, villages, industrial towns and the entrance of factories and significant industries of GPRSs, any disruption of which can cause irreparable or costly damage (Zarei et al., 2017). These stations are usually built outside the city, so access to them is difficult. On the other hand, the safety and monitoring of these stations are vital. The accurate modeling of these stations can provide a great deal of their safety and control because a half-hour disturbance at the gas pressure reduction station can result in consequences for up to several days, depending on the volume of subscribers that use the station's output.

Injuries and disruptions in the performance of CGSs can have different spectra, such as gas pressure drop or total failure of the major part, or all subscribers covered, which in addition to damages to commercial and economic sectors causes dissatisfaction in customers, and in the event of continued cessation of gas, it can even lead to social and security crises. Besides, some technical problems in the event of non-timely control and corrective actions can lead to the fire, explosion, and environmental pollution leakage, which is a significant time to take action appropriately for some incidents.

Expert systems (ESs) are recognized as an implicit knowledge-based research methodology and have different types of applications in industry and scientific research, such as interpretation, detection, controlling the process and classification systems (Wanger, 2017). An ES has been developed to evaluate the performance of a four-factor model of human, safety, health and environmental factors in a gas refinery to assess the effectiveness of ESs in the energy sector (Azadeh, 2008).

The ES to develop a methodology for controlling multivariate predictions, oil and gas reliability is employed in the detection of non-destructive tests and automated control processes (Zemenkov et al., 2015). The ES in creating a knowledge-based according to the rules defined by the speed of engine rotation and its combination, the mathematical models efficiently control the speed of the GEHP engines and, by changing the engine parameters, results in better performance and more suitable adaptation (Wang, 2013).

Afghan et al. (2006) presented a conceptual framework for designing an ES for monitoring and troubleshooting the combustion chamber of gas turbines. An ES was designed to accurately determine the dew point of a dense gas reservoir pressure that was based on the machine learning of an intelligent RBF-based system. In this study, the output has been compared with similar works that estimated the dew point of LSSVM and artificial neural networks (ANNs), and using the statistical parameters, AARD, RMDE, R2, STD, has shown that the RBF method has better performance (Rostami-Hosseinkhani et al., 2014). A model was provided for fracturing risk management concerning crude oil pipelines using a synthesized methodology based on expert judgments and AHP (Noor, 2010).

Sun et al. (2011) used the fuzzy ES to classify jet fuel types. The fuzzy ES showed high performance in identifying fuels. Shafik et al. (2004) developed an ES to automatically investigate the process of welding on pipelines to predict potential defects. Proposed decision support system (DSS) model could lead to a significant reduction in the cost of the inspections and, at the same time, increase the quality of qualitative assessment by acquiring knowledge of radiographic films. Zheng and Chen (2005) presented a fuzzy method to investigate oil and gas pipeline defects based on FTA. The primary sources of failure and disruption in the pipeline were identified using fuzzy decision tree analysis. The designed model was capable of identifying risk factors. To perform a fuzzy tree evaluation, a set of factors and sets of weights were obtained. Experimental results had shown that the proposed method provided a useful control model for the system and could detect failures in oil and gas pipelines before it occurred.

Azadeh et al. (2008) have presented a fuzzy decision model for assessing health, safety, ergonomics and environmental assessment criteria for a gas refinery system. This model was designed using a fuzzy rules-based ES model. Babichev et al. (2010) presented a statistical model for failure analysis in terms of technology and safety conditions for high voltage pump components. Historical error data was used to describe the probability of failure and potential points. El Abbasi et al. (2014) considered a developed model of ANNs that was based on the data from the historical inspections of the Qatar Marine Lines. The proposed model was validated with a capability of over 97%.

The gas transfer value in a CGS was predicted by two methods of ANN and artificial neural fuzzy inference system and compared the efficiency of these two methods in predicting the gas transfer value (Aramesh et al., 2014). Certified systems have been developed to estimate the dew point pressure as one of the parameters influencing gas resources by Rostami et al. (2014). In this system, the genetic algorithm (GA) was based on the ANN and coding has been done with MATLAB software. Dew point pressure is one of the critical parameters in the development of condensate reservoirs.

Tartar et al. (2014) provided a robust solution based on the ES and GA for predicting the saturated gas content for water penetration in gas reservoirs. In this research, the CMIS technique, a combination of RBF, MLP, LSSVM techniques, and GA has been used. Zabihi and Taghizadeh (2015) regarded the amount of energy lost due to pressure reduction in the CGSs; when the gas pressure was lowered, it decreased, and it should be heated to prevent the freezing of the gas raised its temperature. Kim et al. (2017) presented a hybrid model using a rule-based ES and a linear-based mapping technique for detecting the early failure. Tang et al. (2018) proposed a hybrid fuzzy ES model and a scoring method for analyzing the safety status and setting up a warning system at gas/oil maritime facilities. In this model, crisp outputs were considered as safety factors and as performance evaluation frameworks. The performance of the proposed model has been confirmed on the operational data of 10 gas/oil facilities system in Malaysia.

Sukharev et al. (2018) proposed parametric computer models and global gradient method for optimal control of large-scale gas supply systems. The model was used to analyze gas flow in the pipeline system. The result of a case study confirmed the adequacy of the proposed modeling framework. Li et al. (2018) employed a nonlinear steady-state thermodynamic model for fault diagnosis of gas turbines. The modeling framework was tested in several degradation scenarios. The numerical results validated the advantages of the proposed approach in detecting, isolating, and quantifying the degradation of major engine gas components.

Yazdi et al. (2019) proposed an ES for improving the reliability of a spherical hydrocarbon storage tank. The designed ES accounts for the uncertainty of domain experts' by employing the concept of Z-numbers. The empirical experiments confirmed the efficiency of the proposed ES in generating highly reliable failure probability. Chojnacki et al. (2019) proposed an integrated ES and Bayesian network for fire safety examination in nuclear sites. The proposed modeling framework enabled the early diagnosis of faults and provided practical reasoning and diagnostic inferences.

Fuzzy theory is widely used in the gas industry as well as in other similar industries. Since there is inherent uncertainty in input data and judgment of experts, the ES has been modeled through the theory of fuzzy sets. Also, the measurement of useful variables on control of urban gas stations required consideration of uncertainty intervals.

In this paper, a new approach based on an ES and fuzzy logic using the methods of providing knowledge, including the framework and rules, is presented in uncertainty conditions. For effective monitoring of processes of CGSs, a new combination of procedural and descriptive rules and regulations is presented. By combining rules according to experts' opinions and using the frame in defining classes and inherent relationships, complex relationships are modeled between the system's components. Finally, a case study in Iran is presented, and the proposed ES is implemented.

Contributions of the present research are: Firstly, as a system approach, this research develops a new fuzzy ES for CGSs for integrated analysis of automatic shutoff valve and safety valve. Secondly, the design and implementation of the ES are done in an object-oriented, fully parametric and dynamic method. The ES is written in C# programming language, which increases the flexibility of the modeling. Thirdly, many rules are extracted to control the system performance based on fuzzy input data effectively. The proposed ES utilizes decision trees and controls flowcharts for both in periodic control and maintenance in an emergency condition. Given the input from the user and using the knowledge base, the system is capable of evaluating all possible scenarios to provide reasonable arguments for the failure identification and elimination of the various components of a CGS.

The structure of the paper is as follows: Section 2 presents the problem definition and model assumptions. In section 3, basic concepts of the fuzzy ES are presented. In section 4, the modeling's framework is described in detail. Results and discussions are given in section 5. Finally, the conclusion is drawn in section 6.

2- Problem definition

The processes of a gas pressure reduction station are as follows: For the safety of stations, when the regulator gas flow pressure exceeds 20% of the desired amount of pressure, this gas will shut off the gas path and will only be manually placed in the stations current. After the shutoff valve, the regulator is located in the line, which is responsible for reducing gas pressure from 1000 to 250 psi. To control the performance of each regulator, a pressure gauge measures the amount of gas pressure. After the gas passes from the regulator, the gas enters the safety valve. When the output gas pressure from the regulator exceeds 15% of the prescribed pressure, the safety valve is opened and slightly discharged from the gas. Unlike the shutoff valve, the safety valve operates automatically on the line.

2-1- Safety valves

In a facility where pressure is presented, which operate by fluid pressure and temperature, it is sometimes possible that the control devices fail and do not perform their task correctly. As a result, the pressure of the devices increases. In this case, a reliable breaker pressure must be installed in critical areas where necessary to prevent damage to devices, explosions, bursting and, consequently, personal, and financial damage. Many electronic, pneumatic and hydraulic systems are available to control the changes in temperature, pressure and flow rates. All of these systems require an energy source, such as electricity or compressed air to operate. Therefore, other devices are needed to operate and maintain safety at all times, even when the power failure and inefficiency of the above systems are in place.

To prevent such accidents, in addition to controllers, another device called the safety valve is installed on pressurized devices; if pressurized, it will be automatically opened and by removing some of the content. The device will lower its pressure to the limit. In general, valves are devices that are used to adjust and control the flow of fluids that are different in terms of shape, size, or compression to operate, which are the basis for their selection in the equipment.

2-2- Types of safety valves

Pressure safety valves are closed in normal and unusual circumstances, when a certain limit, open negatively or positively exceed the pressure of the installations connected to them and, by evacuating or entering the fluid, again provide safe and normal conditions and blocked again as depicted in Fig. 1. To create safe conditions, these valves must be operated automatically, except in specific processes that, in addition to being automated, it can be opened by an external power.

The safety valves open up when they increase a certain amount of their upstream pressure, and once the pressure drop is reset at the pressure, they are again blocked; they are repeatedly opened and usually work with condensing fluids, such as gas and steam. Besides, safety valves open up with a certain increase in their upstream static pressure, but their opening rates are proportional to the rise in pressure and are often used for incompressible fluids (liquids). In some standards, the term is commonly used, and safety valves work with both liquid and gas fluids, and they are often used for two-phase fluids like fluids with gas.

Fig 1. Type of safety valves

2-3- Conditions of pressure safety equipment

When designing safety systems, designers consider the risk appetite at the bottom of the regulators or the control of the valves, and in light of these conditions, they are placed in the pressure reduction system. The risk factors for designing the pressure safety system are the maximum permissible pressure of the facility, the downstream installation volume, the capacity of the downstream installation, the type and number of installations, the number of persons covered by the pressure reduction, the standards for components, and the design and test history and repairs. For example, in reducing domestic gas pressure due to the low capacity of low gas installations and the lack of expertise of consumers in this sector, the safety system will shut off the gas as soon as the pressure exceeds the prescribed limit. If it is at the station supplying gas to cities and industries where the continuity of gas supply is of particular importance to them, then by first adopting the measures, they will reduce the gas delivery pressure, and then, shut off the gas.

In determining the system’s safety, factors such as the efficiency and ability of regulators, the presence of vibration and stress in the station parts, the number and capacity of regulators, how to position regulators, routine inspections, repair management, station status, and environmental conditions are sufficient.

2-4- Operation of safety valves

The operation of the safety valves can be divided into two forms of direct and indirect operations. In the case of direct operation, the pressure of the gas entering the side of the duct and the pressure from the loading part to the other side is introduced. If the pressure of the gas is more than the load, the valve is in the open position. In valves with indirect function, the valve is used to keep the nozzle open from gas pressure. Another device called a pilot does supply of this pressure. Therefore, they are licensed to this category of the pilot’s valves and their function. The pilot is also in two ways with back pressure and no back pressure.

2-5- Pressure shut-off valves

Pressure shutoff valves are equipment for pressure reduction stations that are closed at the desired pressure setting and cause the entire network to be disconnected, but they are opened manually (Fig.

2). These valves are arranged so that if the valve does not operate the safety valve while operating more than the working class, or if the operation does not cause the line pressure drop to be as defined, it will shut off the station gas.

Fig 2. Pressure shut-off valve

3- Fuzzy expert system

Fuzzy logic originally proposed by Lotfi Zadeh (1965) to model the data ambiguous using truth values and linguistic variables (Bělohlávek et al., 2017). In contrast with Boolean logic, the truth values may be any real number between 0 and 1. In ES application domains, linguistic terms, such as pressure or temperature, can be used as non-numeric values to facilitate the expression of rules and facts (De Aguiar et al., 2018).

One of the most important solutions for artificial intelligence (AI) in response to the need for knowledge is ES. An ES is a computer program that simulates the decision-making technique of an expert person. When the domain of knowledge is defined for an ES, it comes with a reason or conclusion in the same way that experts find solutions to this problem (Poli and Boudet, 2018; Chahal and Singh, 2017). ESs are often dependent on the conclusion to arrive at a logical solution.

The fuzzy ES is one of the branches of AI that works as an expert with a wide range of specialized knowledge to solve problems, e.g., data analysis, prediction, linear and nonlinear control, operations research, pattern recognition, and financial models. It refers to an intelligent computer program that uses knowledge and deduction methods to solve problems that require human experience and skill due to their difficulty. Therefore, the ES is a computer system based on the fuzzy logic that mimics the ability of decision makers. The general structure of a fuzzy system can be listed as follows (Zadeh, 1988):

(1) Fuzzification: in this step, the membership functions are defined based on the input variables to determine the degree of truth for each rule.

(2) Inference: in this step, the truth values are computed, and applied to the conclusion part of each rule. The output is one fuzzy subset to be allocated to each output variable for each rule.

(3) Composition: in this step, all of the fuzzy subsets defined on each output variable are joined together to create a single fuzzy subset for each output variable.

(4) Defuzzification: in this step, a conversion procedure is used for the fuzzy output set.

An important part that uncertainty can enter into ESs is the need to provide ambiguous terms that are widely used in natural language. Using ambiguous terms and interpreting them by computer is difficult. This problem can be solved by fuzzy logic (Liao and Lee, 2004; Hettiarachchi et al., 2016). Fuzzy logic introduces methods for presentation and inference with vague terms as depicted in Fig. 3. In fuzzy sets theory, linguistic variables are used to describe variables. In practical systems, information emanates from two different sources. One of these resources is the experts who are talking about their knowledge for the system in a natural language. Another source is the precise measurement tools that calculate values using physical rules or mathematical model.

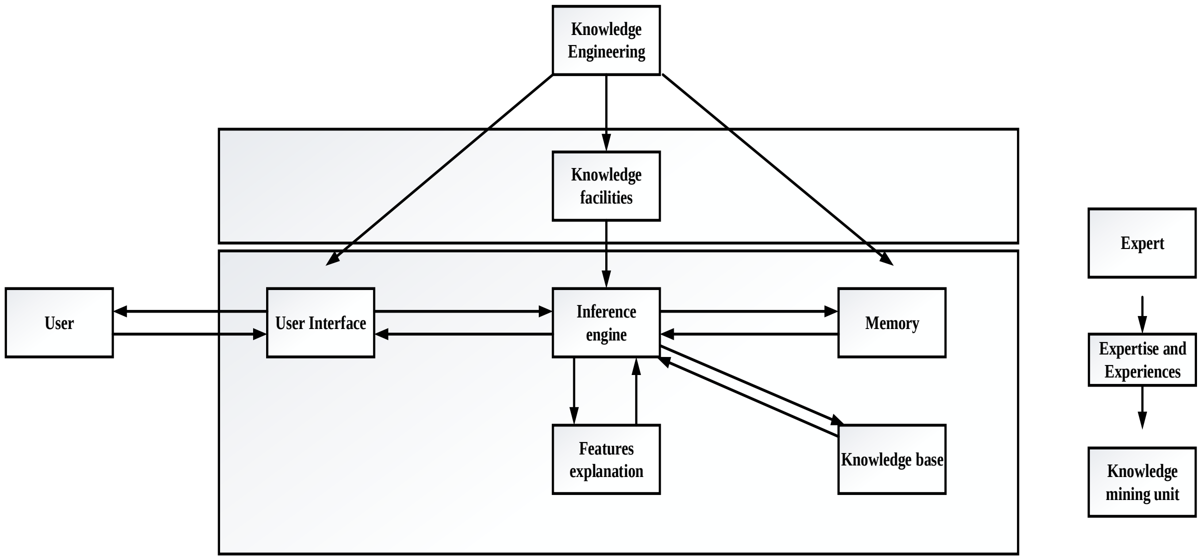


Fig 3. Presented expert system

Uncertainty investigation methods in ESs include numerical methods as well as logical (non-numerical) methods (Ratnayake, 2014). In the presented study, the certainty factors (CFs) method has been used to model the problem in uncertain conditions (Azadeh, 1983). In numerical approaches, the degree of uncertainty is determined by the respective weights. A conventional method for managing vague and inaccurate data is using the CF. In this method, a CF is assigned to each truth that determines its degree of certainty. The CF indicates the degree to which we believe in a fact.

In situations where both observations and knowledge-base are uncertain, the CF is usually employed to express the degree of certainty of them. In determining CF, various rules are as follows:

- In determining the community CF of two assumptions, their most significant CF is selected.
- In deciding the CF for the union the two assumptions, their smallest CFs are selected.
- Some acceptance and non-acceptance criteria are assigned to the CFs as defined below:

$$
\begin{array}{ll}
MB(H,E)=max[P(H|E),P(H)]-P(H) & if\ P(H)<>1 \\
\quad =1 & if\ P(H)=1 \\
MD(H,E)=min[P(H|E),P(H)]-P(H) & if\ P(H)<>0 \\
\quad =1 & if\ P(H)=0 \\
CF(H,E)= MB\ (H,E)-MD(H,E) &
\end{array}
$$

Certainty factor = the rate of belief increase – the rate of increased anti-belief

The process of working with knowledge, facts, and problem-solving strategies to arrive at a result is reasoned. Varied methods of reasoning for dealing with knowledge, facts, and problem-solving strategies include inferential, inductive, abstract, deductive, and common sense. The process of the deductive reasoning is from the whole to component (Jang, 1993). The forward chaining is the inference method that begins with a set of known facts, and new events are generated using rules that are applied to the facts. This process continues until a rule can no longer be used in the inference process. In the forward chaining, the rules are checked from the beginning to the end; if the condition is correct, then, the test is activated. The backward chaining starts from the result and tries to conclude by proving the condition. In the backward chaining, the inference strategy works to test the theory by gathering relevant information (Wang and Elhag, 2008). Inference networks provide a graphical representation of system rules. Having precedence and sequence of rules that appear in the form of nodes and the relationship between them is indicated by the connection between the nodes. Another rule precedes the sequence of some supportive rules; therefore, they can be linked.

And finally, the proposed fuzzy ES is composed of:

1) Database,
2) Rule base for the definition of linguistic variables, phrases, and rules,
3) Knowledge base,
4) User-friendly graphical interface that provides full-time access for operators throughout the day,
5) Fuzzification module for processing of fuzzy input variables,
6) Inference engine for assessment of expert's opinions, and
7) Defuzzification module for processing of the output variables.

4- Research methodology

The decision tree is a representation of knowledge and is also a way of reasoning about knowledge. The decision tree features include self-learning power, which can dynamically and continuously add a new node, branch, and new leaves to the tree. Decision making structures can be converted into production rules (Polat and Güneş, 2007). To demonstrate knowledge in the form of rules, firstly, knowledge of experts as a decision tree for controlling emergencies and control charts are presented for the detailed and periodic control of safety valves and shutoff valves as given in figures 4 and 5.

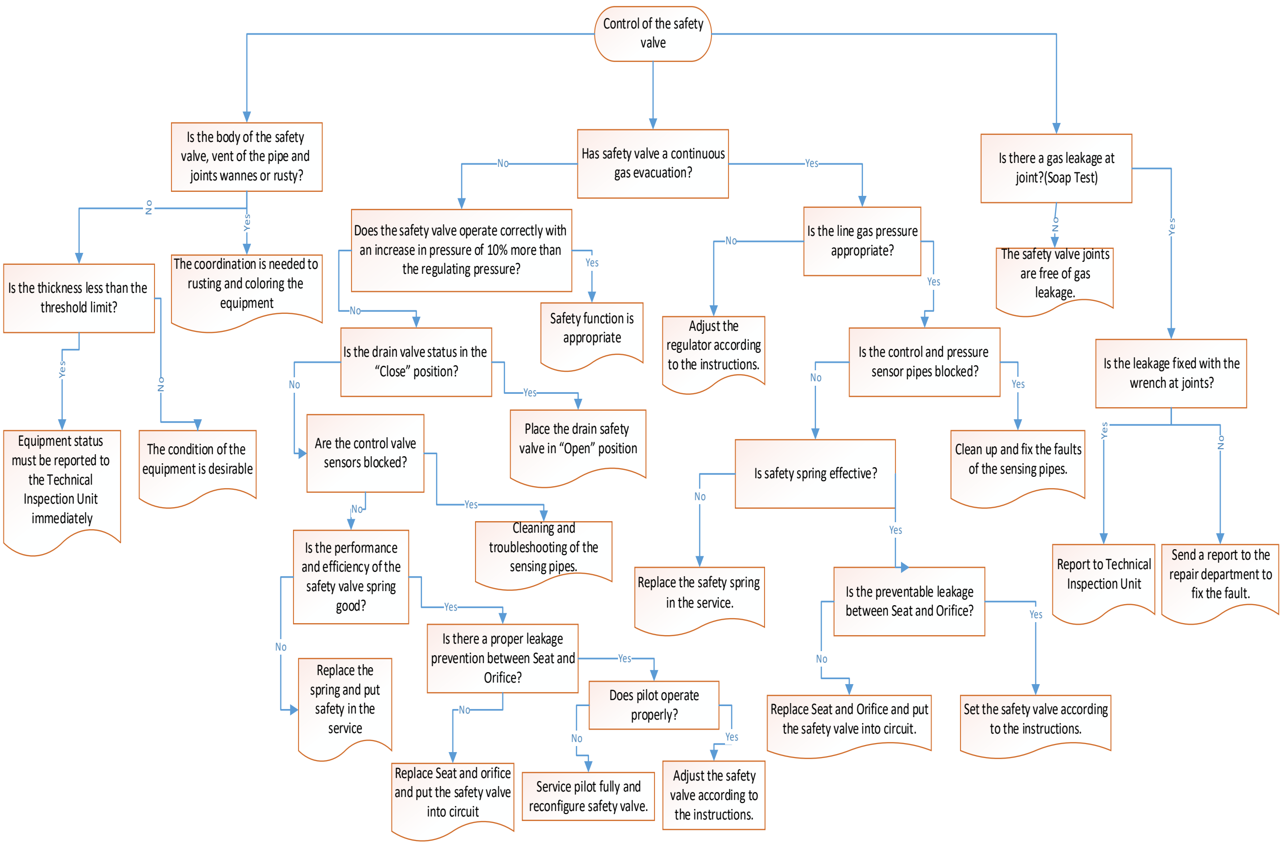


Fig 4. Decision tree and control flowcharts for the validity of safety valves

A flowchart depicts the sequence of steps to perform a particular operation (Ebersbach and Peng, 2008). This approach is a standard technique in conventional programming, which uses graphical representation to show the sequence of operations. The blocks represent specific operations, decisions. The relationship between the blocks shows its executive order. Flowchart technology analyzes and evaluates itself and can easily connect to an ES.

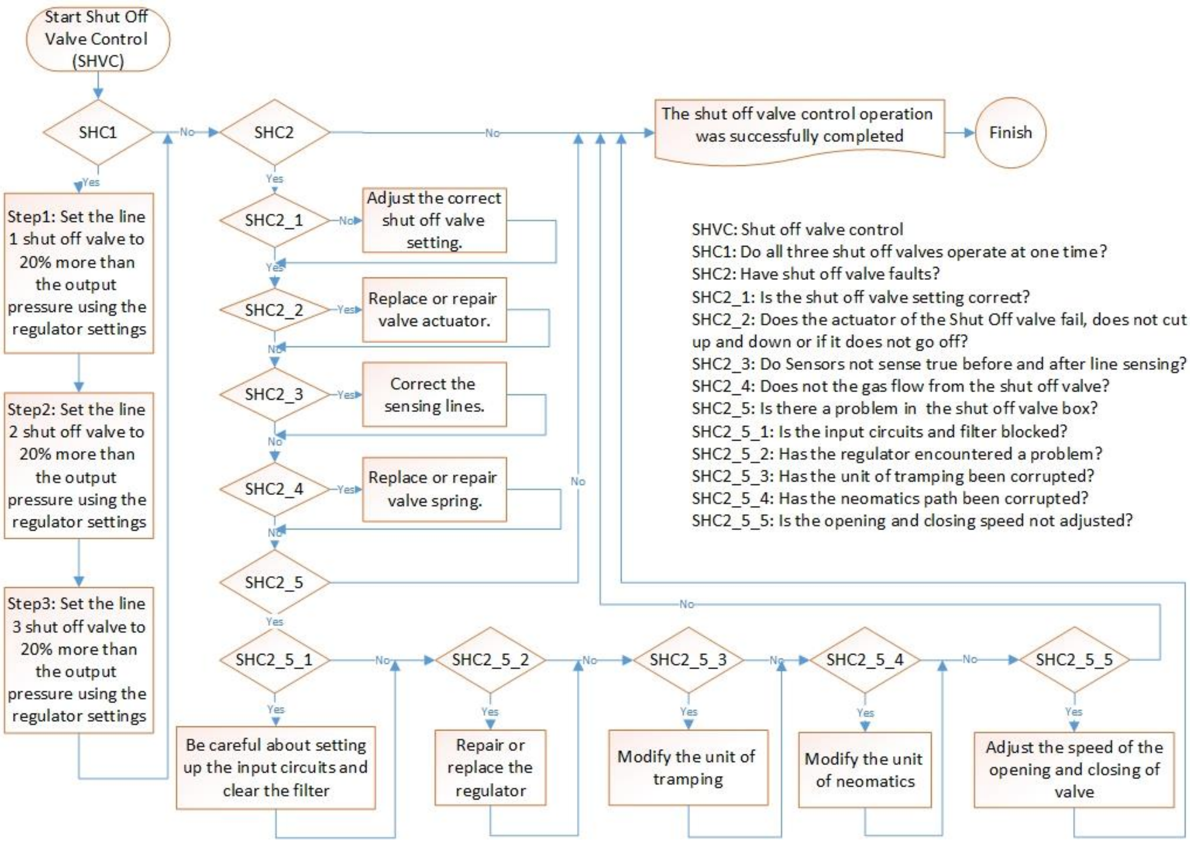


Fig 5. Decision tree and control flowcharts for the operation of the shut-off valves

4-1- Variables

In this research, the ES uses the following input data that changes over time and is vital for the system to control and fault detection the main components of the gas pressure reduction station. The designed system is capable of controlling the main parameters of the CGSs and improving the safety factors to prevent accidents and minimize its harmful effects. For example, for pipeline corrosion, the cathodic protection system has been investigated, and corrective action has been taken to prevent leakage or explosion. The proposed system can also help to reduce environmental damage by preventing methane leaks as one of the most destructive greenhouse gases. This system controls the parameters of the reduction of greenhouse gas emissions from combustion. By preventing mercaptan leak, there will be no harmful effects on the health of workers and the environment.

4-2- Fuzzy input variables

In this section, the definition of fuzzy variables is associated with linguistic terms and their membership and domain functions. The first step in the processing of the ES is to phase out the inputs of the system (Iqbal, 2007). The process of phasing out uncertain input data is used to transform into linguistic variables that can be implemented by experts' rational judgments. Linguistic variables in fuzzy systems, like mathematical variables, are used to describe the variables, such as temperature and pressure. However, a mathematical description of a variable of numbers is used, but a fuzzy description of a linguistic variable with language descriptions such as low, high, very high, negatively, moderate positive, etc (Thaker and Nagori, 2018; Ross, 2010; Zimmermann, 2012) as given in figure 6 with CFs, and tables 2 and 3.

Table 1. Input variable of the presented ES model

Input variables	
1- Input-Pressure	6- Safety-Pressure
2- Input-Temperature	7- Shutoff-Pressure
3- Heater-Gas-Temperature	8- Output-Pressure
4- Heater-water-temperature	9- Output-Temperature
5 – Regulator-Pressure	10- Carbon-Emissions

4-3- Defuzzification variables

Defuzzification is a phase in the implementation of a fuzzy ESs in which fuzzy inference results are converted to real numbers. The defuzzification of variables involves creating a measurable result according to fuzzy logic. In previous research, various methods have been used to defuzzify data. In the model of the ES in this study, the centroid average (CA) method is used to defuzzification information. This selection is based on the initial results from the engine, and this method has yielded better results than other approaches.

In this method, it is assumed that the fuzzy set A' of an alliance or intersection of M is a fuzzy set. Suppose $\bar{y}^h$ is the center of the fuzzy set and w_h of its height. The height of fuzzy sets is defined as the weighted average of fuzzy sets with certain weights. Accordingly, the central average (y') is defined in equation (1).

$$y' = \frac{\sum_{h=1}^{M} w_h \bar{y}^h}{\sum_{h=1}^{M} w_h} \tag{1}$$

Membership functions along with the linguistic term for the fuzzy input variables are illustrated in figure 7.

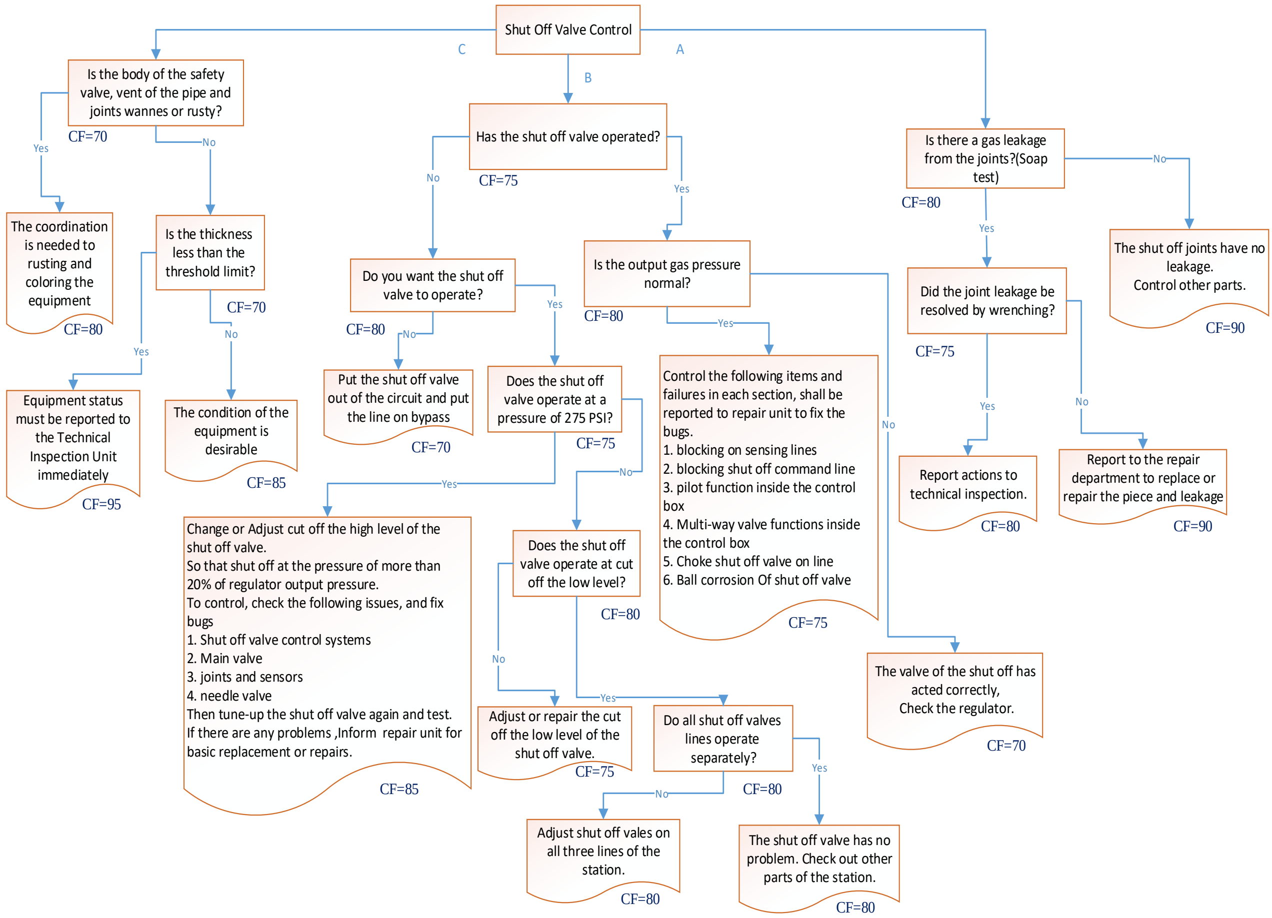
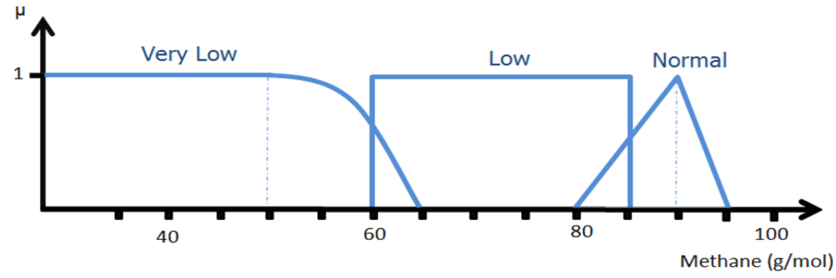


Fig 6. Certainty factors in decision tree and control flowcharts for the operation evaluation of the shut-off valves

Table 2. Different scenarios based on a combination of fuzzy variables

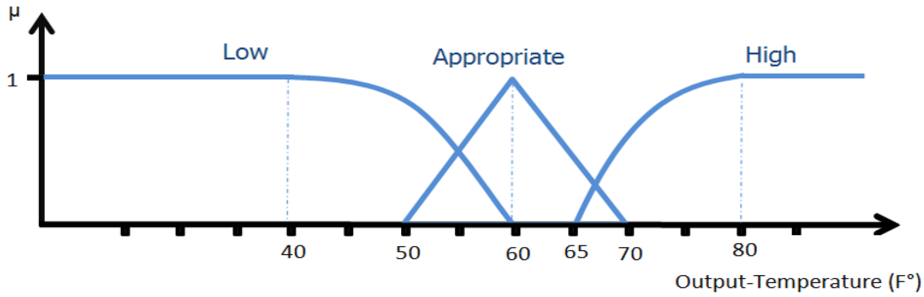
Status	**Input Variables**	**Output Variable**
1	Safety-Pressure & Shutoff-Pressure	Sound-Station
2	Regulator-Pressure	Safety-Pressure
3	Regulator-Pressure	Shutoff-Pressure
4	Safety-Pressure & Shutoff-Pressure	Carbon-Emission



Linguistic Term: Very Low : 50 – 65(g/mol); Low : 60 – 85 (g/mol); Normal : 80 - 90 – 95(g/mol)

Membership Function: *Z* : Very Low; *Pi* : Low; Triangular : Normal

Values of Methan gas (Domain: 0 - 120)



Linguistic Term: Low : 40 – 60(F°); Appropriate : 50 – 60 – 70(F°); High: 65 – 80(F°)

Membership Function: Z : Low; Triangular : Appropriate; S : High

Output temperature (Domain: 0 - 100)

Fig 7. Membership functions of fuzzy variables

5- Result and discussion

To establish a reliable fault diagnosis system, this research has presented a new fuzzy ES model for controlling and troubleshooting components of a CGS. The applicability of the ES has been maximized by the incorporation of the knowledge of experts specializing in various fields including mechanical, chemical, electrical, instrumentation, safety, and environmental engineering. The designed fault diagnosis system is capable of controlling the two main components of the CGS in case of periodic control or an emergency.

Due to the specifications of the designed ES, timely notification and follow-up are provided in cases where the interference factor is outside the station's pressure reduction range. For example, the ES, by observing an increase in the filter pressure difference, recommends that the filter should be cleaned or replaced as soon as possible so that the gas flow cannot be stopped.

Table 3 shows the linguistic terms for some essential scenarios. For example, table 3a illustrates the linguistic terms for regulator-pressure as an input variable and safety-pressure as an output variable. Table 3b provides the linguistic terms for shutoff-pressure and safety-pressure as input variables and sound-station as an output variable. Based on the data presented in table 3, some examples of the fuzzy descriptive if-then rules system are specified as follows:

Example 1 (safety indicator)
IF *Regulator-pressure* **IS** High,
THEN *Safety-pressure* **IS** Hi AND Call Regulator Control (RC)

Example 2 (safety indicator)
IF *Safety-pressure* **IS** Normal,
AND *Shutoff-pressure* **IS** High
THEN *Sound-station* **IS** Inappropriate **AND** Call Shut off valve control (SHVC)

Example 3 (safety indicator)
IF *Safety-pressure* **IS** High,
AND *Shutoff-pressure* **IS** High
THEN *Sound-station* **IS** critical **AND** Call RC & SVC & SHVC

Table 3. Some fuzzy rules based on linguistic terms (a - d)

a)

Input variables	**Output variable**	
Regulator-pressure	Safety-pressure	Action
Low	Low	Call RC
Normal	Normal	-
High	High	Call RC

RC: Regulator Control

b)

Input variables		**Output variable**	
Safety-pressure	Shutoff-pressure	Sound-station	Action
Low	Low	Normal	-
	Normal	Normal	-
	High	Inappropriate	Call SHVC
Normal	Low	Normal	-
	Normal	Normal	-
	High	Inappropriate	Call SHVC
High	Low	Inappropriate	Call SVC
	Normal	Inappropriate	Call SVC
	High	Inappropriate	Call SHVC+ SVC

SHVC: Shut off valve control; SVC: Safety valve control

c)

Input variables	**Output variable**	
Regulator-pressure	Shutoff-pressure	Action
Low	Low	Call RC
Normal	Normal	-
High	High	Call RC

RC: Regulator control

d)

Input variables		**Output variable**	
Safety-pressure	Shutoff-pressure	Sound-station	Action
Low	Low	appropriate	-
	Normal	appropriate	-
	High	appropriate	Call RC & SHVC
Normal	Low	appropriate	-
	Normal	appropriate	-
	High	appropriate	Call RC & SHVC
High	Low	appropriate	Call RC & SHVC
	Normal	appropriate	Call RC & SHVC
	High	critical	Call RC & SVC & SHVC

RC: Regulator Control; SHVC: Shut off valve control; SVC: safety valve control

The validation process in this study is targeted at knowledge acquisition validation, and functional validity checking through user requirements analysis. Knowledge validation involves the verification of all the knowledge extracted from the experts. In this step, the knowledge base has to be systematized creating a conceptual model. This process includes all the interdependencies between the task elements, besides the processes used by the expert to perform this step. The validation of the known properties requires extra knowledge exclusively for validation, not for the deduction. To validate the designed ES, the knowledge base has been designed and implemented based on the experts' opinions. Also, by receiving feedback from the trusted experts (i.e., other experts who did not take part in the compilation of the knowledge base), the rules extracted from the ES have been validated.

Behavior validation is another approach to verify the ES outputs. This process involves testing for an effective checking of user requirements. Several test cases can be defined to check specific conditions. In the present study, a Turing test is employed which involves the evaluation of the model output mixed with approvals of human experts for a set of given cases. A set of independent experts in the field of gas transmission and safety analysis were selected to act as evaluators. The evaluators have checked the accuracy of the rules and overall utility of the designed ES. To identify invalid outputs in the ES, various scenarios have been tested in this study, using the combination of input variables. Based on the sensitivity analysis of the ES, no invalid output was generated in any of the scenarios of a combination of different input variables. For instance, the output pressure from the station cannot be higher than the input pressure of the station. Also, the temperature of the outlet gas from the station cannot exceed the temperature of the exhaust gas from the heater. For this purpose, a control subroutine was programmed in the C# application environment to determine these logical relations and to check the validity of outputs of the designed ES. The designed ES provides an acceptable diagnosis for all typical cases.

After verifying the rules by the experts, to validate the output of the fuzzy ES, different scenarios were compared with the output of MATLAB software. For example, an analysis of the sensitivity of the output pressure in terms of the inlet pressure in the pressure regulator states is given to PSI 200, and PSI 250 (Tables 4 and 5). Based on the outputs obtained, the deviation of the results between the ES model and MATLAB is not significant, and the validity of the outputs are confirmed.

Table 4. Sensitivity analysis of the pressure output according to regulator pressure (200 psi)

Input pressure	Output pressure	
	Expert system	MATLAB
100	93.6	92.4
200	93.6	100
300	227.5	227
400	227.5	227
500	227.5	227
600	227.5	227
700	227.5	227
800	227.5	227
900	227.5	227

Table 5. Sensitivity analysis of the pressure output according to the regulator pressure (250 psi)

Input pressure	Output pressure	
	Expert system	Expert system
100	93.6	93
200	93.6	100
300	227.5	227
400	231.5	230
500	248.3	248
600	248.3	248
700	248.3	248
800	248.3	248
900	248.3	248

6- Conclusion

In this paper, we tried to consider the design and implementation framework of a fuzzy expert system (ES) for controlling and troubleshooting the safety valves and shutoff valve of pressure reduction stations, namely CGSs. This research is based on a real case study in the gas industry in Iran. Because the structures of CGSs are largely similar, data from experts in two provinces were used. The range of knowledge used by the experts is very extensive and includes field studies as well as the interview with Ilam Gas Company's experts with 14 CGS and some stations in Semnan Province with 41 CGS. The knowledge-based design system in CLIPS software environment can extract procedural and descriptive rules based on experts' opinions to analyze the complex relationships between mechanical and physical components of gas pressure stations. The proposed system operates through the fuzzy sets theory due to the possibility of considering uncertainties in input data that relates to experts' judgments and is widely used in the gas industry as well as in other similar industries. A new hybrid fuzzy ES, consisting of a variety of knowledge display techniques, was designed and implemented to prevent the control of CGSs under uncertainty conditions in terms of periodic control and emergency conditions. The proposed system works through the fuzzy logic and certainty factors due to the possibility of considering inconsistencies in input data that relates to the judgments of experts in the gas industry. In this research, the safety valve and shutoff valve have been investigated and fully implemented in the presented fuzzy ES. Due to the complexity of the issue, effective monitoring of the performance of CGSs was mainly focused on certain aspects of safety process such as the failure of the main elements, the improvement of safety from the viewpoint of strengthening the components of the hardware, or the development of control systems without the knowledge of expertise. A potential problem in current control systems for the country's gas industry is that these systems rely to some extent on experts' judgments. The judgments cannot always provide consistent results. Besides, the availability of specialists during an accident and the occurrence of unforeseen events at CGSs is crucial, and the absence of specialists or the repair team often disrupts the safety performance assessment system of the stations and may have irreversible human effects, environmental, and social issues. As a result, existing systems for managing the safety of gas pressure reduction station are of limited effectiveness in ensuring the performance and upgrading of the controlled condition. The use of a fuzzy ES involves the rules and opinions of experts in the decision-making process; in this way, obscure or uncertain information can be processed. As a result, the implementation of this ES creates a reliable and alarming control system for transmission and gas pressure reduction station. In addition to providing a smart model for preventive safety management at CGSs through periodic component control, the reactive approach and rapid decision-making of experts' decisions in emergencies have been considered. The proposed ES design offers an AI model based on the expertise of different experts, a comprehensive approach to monitoring the safety performance of CGSs. This ES has been completely coded in the fuzzy environment of the Clips software. Since existing models for controlling CGSs at the operational level are mainly implemented in certain conditions and a set of input variables (such as temperature and pressure variables) are limited; they can describe the ambiguity in the data as well as considering the inherent complexity of the relationships between components of the station. In this research, we tried to design a comprehensive knowledge-base, taking into account all operational aspects of the control of safety valves and shutoff valves. The ES inference engine can invoke decision tree procedures and decision-based flowcharts based on a set of questions and answers with the user. The main goal of the proposed ES can be to save on the cost of inspection and maintenance of repairs and also the possibility of making more precise decisions on periodic monitoring of the status of valves, improvement of stations' safety conditions and occupational health indices, including environmental pollution and gas leakage, improving the speed of implementation of corrective measures in emergency situations through quick question-and-answer with the user and also full-time access to the experts. The results of this research can be provided in the form of a software application which is accessible to experts and practitioners directly that they are in the gas industry, and teams of control and inspection of CGSs. To implement the fuzzy ES, the necessary data are provided through interviews with experts in various fields including mechanics, chemistry, electricity, instrumentation safety, environment, and experiences of technicians from provincial gas assistance and repairs as well as engineers and operation managers, technical inspections, engineering services, and HSE. By combining different input and output variables to extract the if-then fuzzy rules, the combination of these scenarios has been extracted over 164 for periodic control as well as for emergency control. A significant number of these rules are regarded that are related to controlling station safety and reducing environmental degradation. In this way, the implementation of the ES is directly effective in improving the level of safety and controlling environmental damage at the CGSs.

The validation process in this study was targeted at knowledge acquisition validation, and functional validity checking through user requirements analysis. To validate the designed ES, the knowledge base has been designed and implemented based on the experts' opinions. Also, by receiving feedback from the trusted experts (i.e., other experts who did not take part in the compilation of the knowledge base), the rules extracted from the ES have been validated. Behavior validation was also implemented for an effective checking of user requirements based on several test cases. After verifying the rules by the experts, to approve the output of the fuzzy ES, different scenarios were compared with the output of MATLAB software. The sensitivity analysis was carried out by measuring the output pressure in terms of the inlet pressure in the case of PSI 200, and PSI 250. Based on the outputs, the deviation of the results between the ES model and MATLAB was not significant, and the validity of the outputs was confirmed.

The future study must aim at integrating the artificial intelligent and fuzzy ES for more effective control of the system components. Some of the modeling characteristics of the ES can be extended to address a more realistic situation. For example, sustainability factors can be added to the inference engine for obtaining more realistic control procedures. It is also interesting to develop the ES by setting up a national monitoring room to control consumption points and instant decisions for crisis management. From the hardware point of view, some data of the system can be received directly by sending from the remote terminal unit (RTU), and thus, there is no need to manually enter the information by the operator. By using a sensor and electronic board that receives and sends remote information, the decision maker can receive system information automatically, e.g., pressure and temperature, and other parameters. Future research can also examine the extension of the fuzzy ES to apply to other domains, e.g., gas pipelines failure analysis and design optimization of a gas pressure reduction stations.

Acknowledgments

The authors gratefully acknowledge the reviewers for their constructive comments in the earlier draft of this research.

References

Afgan, N.H., Carvalho, M.G., Pilavachi, P.A., Tourlidakis, A., Olkhonski, G.G. and Martins, N., (2006). An expert system concept for diagnosis and monitoring of gas turbine combustion chambers. Applied Thermal Engineering, 26(7), pp.766-771.

Aramesh, A., Montazerin, N. and Ahmadi, A., (2014). A general neural and fuzzy-neural algorithm for natural gas flow prediction in city gate stations. Energy and Buildings, 72, pp.73-79.

Azadeh, A., Fam, I.M., Khoshnoud, M. and Nikafrouz, M., (2008). Design and implementation of a fuzzy expert system for performance assessment of an integrated health, safety, environment (HSE) and ergonomics system: The case of a gas refinery. Information Sciences, 178(22), pp.4280-4300.

Babichev, S.A., Bychkov, E.V. and Kryukov, O.V., (2010). Analysis of technical condition and safety of gas-pumping units. Russian Electrical Engineering, 81(9), pp.489-494.

Bělohlávek, R., Dauben, J.W. and Klir, G.J., (2017). Fuzzy logic and mathematics: a historical perspective. Oxford University Press.

Chahal, R.K. and Singh, S., (2017). Fuzzy rule-based expert system for determining trustworthiness of cloud service providers. International Journal of Fuzzy Systems, 19(2), pp.338-354.

Chojnacki, E., Plumecocq, W. and Audouin, L., (2019). An expert system based on a Bayesian network for fire safety analysis in nuclear area. Fire Safety Journal, 105, pp.28-40.

De Aguiar, J., Scalice, R.K. and Bond, D., (2018). Using fuzzy logic to reduce risk uncertainty in failure modes and effects analysis. Journal of the Brazilian Society of Mechanical Sciences and Engineering, 40(11), pp.516-527.

Ebersbach, S. and Peng, Z., (2008). Expert system development for vibration analysis in machine condition monitoring. Expert systems with applications, 34(1), pp.291-299.

El-Abbasy, M.S., Senouci, A., Zayed, T., Mirahadi, F. and Parvizsedghy, L., (2014). Artificial neural network models for predicting condition of offshore oil and gas pipelines. Automation in Construction, 45, pp.50-65.

Gholizad, A., Ahmadi, L., Hassannayebi, E., Memarpour, M. and Shakibayifar, M., (2017). A system dynamics model for the analysis of the deregulation in electricity market. International Journal of System Dynamics Applications, 6(2), pp.1-30.

Hettiarachchi, C., Do, H. and Choi, B., (2016). Risk-based test case prioritization using a fuzzy expert system. Information and Software Technology, 69, pp.1-15.

Iqbal, A., He, N., Li, L. and Dar, N.U., (2007). A fuzzy expert system for optimizing parameters and predicting performance measures in hard-milling process. Expert Systems with Applications, 32(4), pp.1020-1027.

Jang, J.S., (1993). ANFIS: adaptive-network-based fuzzy inference system. IEEE transactions on systems, man, and cybernetics, 23(3), pp.665-685.

Kim, D., Lin, Y., Lee, S., Kang, B.H. and Han, S.C., (2017). A hybrid failure diagnosis and prediction using natural language-based process map and rule-based expert system. International Journal of Computer, Communications and Control, 13(2), pp.175-191.

Krichene, N., (2002). World crude oil and natural gas: a demand and supply model. Energy economics, 24(6), pp.557-576.

Kryukov, O.V., (2012). Methodology and tools for neuro-fuzzy prediction of the status of electric drives of gas-compressor units. Russian Electrical Engineering, 83(9), pp.516-520.

Li, J., Zhang, G., & Ying, Y. (2018). Gas Turbine Gas Path Fault Diagnosis Based on Adaptive Nonlinear Steady-state Thermodynamic Model. International Journal of Performability Engineering, 14(4), pp. 751-764.

Liao, Y. and Lee, J.B., (2004). A fuzzy-expert system for classifying power quality disturbances. International journal of electrical power & energy systems, 26(3), pp.199-205.

Noor, N.M., Yahaya, N., Ozman, N.A.N. and Othman, S.R., (2010). The forecasting residual life of corroding pipeline based on semi-probabilistic method. Journal of Civil Engineering, Science and Technology, 1(2), pp.1-6.

Polat, K. and Güneş, S., (2007). Classification of epileptiform EEG using a hybrid system based on decision tree classifier and fast Fourier transform. Applied Mathematics and Computation, 187(2), pp.1017-1026.

Poli, J.P. and Boudet, L., (2018). A fuzzy expert system architecture for data and event stream processing. Fuzzy Sets and Systems, 343, pp.20-34.

Poživil, J., (2004). Use of expansion turbines in natural gas pressure reduction stations. Acta Montanistica Slovaca, 3(9), pp.258-260.

Ratnayake, R.C., (2014). KBE development for criticality classification of mechanical equipment: a fuzzy expert system. International journal of disaster risk reduction, 9, pp.84-98.

Ross, T.J., (2010). Classical Sets and Fuzzy Sets. Fuzzy Logic with Engineering Applications, pp.25-47.

Rostami-Hosseinkhani, H., Esmaeilzadeh, F. and Mowla, D., (2014). Application of expert systems for accurate determination of dew-point pressure of gas condensate reservoirs. Journal of Natural Gas Science and Engineering, 18, pp.296-303.

Rostami-Hosseinkhani, H., Esmaeilzadeh, F. and Mowla, D., (2014). Application of expert systems for accurate determination of dew-point pressure of gas condensate reservoirs. Journal of Natural Gas Science and Engineering, 18, pp.296-303.

Safarian, S., Saboohi, Y. and Kateb, M., (2013). Evaluation of energy recovery and potential of hydrogen production in Iranian natural gas transmission network. Energy Policy, 61, pp.65-77.

Shafeek, H.I., Gadelmawla, E.S., Abdel-Shafy, A.A. and Elewa, I.M., (2004). Automatic inspection of gas pipeline welding defects using an expert vision system. NDT & E International, 37(4), pp.301-307.

Sukharev, M.G., Kosova, K.O. and Popov, R.V., (2018). Mathematical and computer models for identification and optimal control of large-scale gas supply systems. Energy, (Article in press), DOI: 10.1016/j.energy.2018.02.131.

Sun, X., Zimmermann, C.M., Jackson, G.P., Bunker, C.E. and Harrington, P.B., (2011). Classification of jet fuels by fuzzy rule-building expert systems applied to three-way data by fast gas chromatography—fast scanning quadrupole ion trap mass spectrometry. Talanta, 83(4), pp.1260-1268.

Tang, K.H.D., Dawal, S.Z.M. and Olugu, E.U., (2018). Integrating fuzzy expert system and scoring system for safety performance evaluation of offshore oil and gas platforms in Malaysia. Journal of Loss Prevention in the Process Industries, 56, pp.32-45.

Tatar, A., Yassin, M.R., Rezaee, M., Aghajafari, A.H. and Shokrollahi, A., (2014). Applying a robust solution based on expert systems and GA evolutionary algorithm for prognosticating residual gas saturation in water drive gas reservoirs. Journal of Natural Gas Science and Engineering, 21, pp.79-94.

Thaker, S. and Nagori, V., (2018). Analysis of Fuzzification Process in Fuzzy Expert System. Procedia computer science, 132, pp.1308-1316.

Wagner, W.P., (2017). Trends in expert system development: A longitudinal content analysis of over thirty years of expert system case studies. Expert systems with applications, 76, pp.85-96.

Wang, M., Yang, Z., Su, X., Zhang, B., Wu, X. and Shi, Y., (2013). Simulation and experimental research of engine rotary speed for gas engine heat pump based on expert control. Energy and Buildings, 64, pp.95-102.

Wang, Y.M. and Elhag, T.M., (2008). An adaptive neuro-fuzzy inference system for bridge risk assessment. Expert systems with applications, 34(4), pp.3099-3106.

Yazdi, M., Hafezi, P., & Abbassi, R. (2019). A methodology for enhancing the reliability of expert system applications in probabilistic risk assessment. Journal of Loss Prevention in the Process Industries, 58, pp.51-59.

Zabihi, A. and Taghizadeh, M., (2015). New energy-saving temperature controller for heater at natural gas gate station. Journal of Natural Gas Science and Engineering, 27, pp.1043-1049.

Zadeh, L.A., (1983). The role of fuzzy logic in the management of uncertainty in expert systems. Fuzzy sets and systems, 11(1-3), pp.199-227.

Zadeh, L.A., (1988). Fuzzy logic. Computer, 21(4), pp. 83-93.

Zarei, E., Azadeh, A., Khakzad, N., Aliabadi, M.M. and Mohammadfam, I.,(2017). Dynamic safety assessment of natural gas stations using Bayesian network. Journal of hazardous materials, 321, pp.830-840.

Zemenkov, Y.D., Shalay, V.V. and Zemenkova, M.Y., (2015). Expert systems of multivariable predictive control of oil and gas facilities reliability. Procedia Engineering, 113, pp.312-315.

Zheng, X.B. and Chen, G.M., (2005). Research on fuzzy comprehensive evaluation method for oil & gas pipeline failure based on fault tree analysis. Systems Engineering-theory & Practice, 2, pp.139-144.

Zimmermann, H.J., (2012). Fuzzy sets, decision making, and expert systems (Vol. 10). Springer Science & Business Media.

Appendix

Sample codes for safety valves in Clips with CFs

```
(defrule Safety_Valve_Control
(SafetyValve Control)
=>
(printout t "Which part do you want to control?"crlf
"a.external condition"crlf
"b.gas leakage"crlf
"c.gas discharge"crlf
"your answer (a or b or c):"crlf)
(assert(SVC(read))))

(defrule C1
(SVC c)
=>
(printout t "Is the safety valve dischrging the gas continuously?"crlf
"your answer (yes or no):"crlf)
(assert(C1(read))))

(defrule C2
(C1 yes)
=>
(printout t "Is the line gas pressure appropriate?"crlf
"your answer (yes or no):"crlf)
(assert(C2(read))))

(defrule C2_no
(declare (CF 0.95))
(C2 no)
=>
(assert(CC2 no)))


(defrule CC2_no
?f <- (CC2 no)
=>
(printout t "because:"crlf
"the safety valve is dischrging the gas continuously, and"crlf
"line gas pressure is not appropriate"crlf
"with certainty factor of:" (get-cf ?f) crlf
"solve the regulator problem and set it according to manual"crlf))

(defrule C3
(C2 yes)
=>
(printout t "Are control sensing pipes and safety valve command blocked?"crlf
"your answer (yes or no):"crlf)
(assert(C3(read))))

(defrule C3_Yes
```

```
(declare (CF 0.9))
(C3 yes)
=>
(assert(CC3 yes)))

(defrule CC3_Yes
?f <- (CC3 yes)
=>
(printout t "because:"crlf
"the safety valve is dischrging the gas continuously, and"crlf
"line gas pressure is appropriate, and"crlf
"control sensing pipes and safety valve command are blocked"crlf
"with certainfy factor of:" (get-cf ?f) crlf
"clean and solve the sensing pipes problem"crlf))

(defrule C4
(C3 no)
=>
(printout t"Is the performance of safety valve spring appropriate?"crlf
"your answer (yes or no):"crlf)
(assert(C4(read))))

(defrule C4_No
(declare (CF 0.95))
(C4 no)
=>
(assert(CC4 no)))

(defrule CC4_No
?f <- (CC4 no)
=>
(printout t "because:"crlf
"the safety valve is dischrging the gas continuously, and"crlf
"line gas pressure is appropriate, and"crlf
"control sensing pipes and safety valve command are not blocked, and"crlf
"performance of safety valve spring is not appropriate"crlf
"with certainty factor of:" (get-cf ?f) crlf
"replace the spring and put the safety valve in service"crlf))
```

Sample codes for shutoff valve in Clips in a fuzzy environment

```
(defrule shutoff_pressure1
(selected_term 9)
=>
(assert (a8)))

(deftemplate shutoff_pressure
0 350 PSI
(
(low (z 255 300))
(normal (280 0) (300 1) (320 0))
(high (s 310 330))
))
(defrule getdata8
  (declare (salience 100))
(a8)
  =>
  (printout t "Enter shutoff pressure in range of [0 350] PSI: ")
  (bind ?t (read))
  (assert (shutoffpressure ?t)))
(defrule fuzzify8
(shutoffpressure ?t)
=>
(assert (shutoff_pressure (?t 0) (?t 1) (?t 0))))

(defrule R81
(shutoff_pressure normal)
=>
(assert(SOP normal)))

(defrule XR81
?f<-(SOP normal)
=>
(printout t "shutoff pressure is normal with certainty factor of:"(get-cf ?f) crlf))

(defrule R82
(shutoff_pressure low)
=>
(assert(SOP low)))

(defrule XR82
?f<-(SOP low)
=>
(printout t "shutoff pressure is low with certainty factor of:"(get-cf ?f) crlf))

(defrule R83
(shutoff_pressure high)
=>
(assert(SOP high)))


(defrule XR83
?f<-(SOP high)
```

```
=>
(printout t "shutoff pressure is high with certainty factor of:"(get-cf ?f) crlf))


(defrule XSOP
(selected_term 9)
=>
(plot-fuzzy-value t ".+*"nil nil
(create-fuzzy-value shutoff_pressure low)
(create-fuzzy-value shutoff_pressure normal)
(create-fuzzy-value shutoff_pressure high)))
```