Fuzzy Logic Modeling and Controller Design for a Fluidized Catalytic Cracking Unit

Hossein Tootoonchy and Hassan H. Hashemi

Abstract—**This paper examines the procedure for nonlinear modeling and Fuzzy controller design of a Fluidized Catalytic Cracking Unit, also known as FCCU, of Abadan Refinery in Iran. FCCU is one of the most important elements in Petrochemical industry. In 2006 alone, FCCUs refined one-third of the crude Oil worldwide. FCCUs convert the heavy distillates like Gasoil (feed) and Crude Oil to Gasoline, Olefinic gases and other more usable products. Since FCCUs yield large amount of products very efficiently, along with the Petrochemical products' daily price fluctuations, the optimization of such units has always been the focus of attention for engineers as well as investors. Unlike the conventional controllers, Fuzzy Logic is the perfect choice for uncertain, dynamic and nonlinear processes where the mathematical model of the plant cannot be produced, or if realizable, a great deal of approximation is involved. The heuristic approach of Fuzzy Logic controllers is the closest form to human language, and this virtue will make them a perfect candidate for a wide range of industrial applications. The investigations in this paper are simulated and proven by MATLAB Fuzzy Logic Toolbox R2012b. Through this paper, the applicability and promising results of Fuzzy Logic controllers for such a complex and demanding plant will be investigated.**

Keywords — **Fuzzy Logic, Fuzzy Controller, FCCU, Nonlinear Modeling.**

I. Introduction

The Fluidized Catalytic Cracking units are amongst the most important and valuable facilities in Petrochemical plants. FCCUs convert the heavy weight Oil feeds, like Gasoil, into lighter hydrocarbons, which are more valuable and usable for industry. The overall economics of the refinery largely depends on the economic operation of FCCU [1]. The unit consists of two separate, yet interconnected sections; the Riser reactor (Separator) and the Regenerator reactor. The riser reactor is where the cracking process occurs, and the Coke covers the Catalyst and reduces its activity. The regeneration process removes the Coke deposited on the Catalyst and feeds it back to the process [2]. This procedure is perfect for seasonal production throughout the year. Fig. 1 depicts a schematic diagram of an FCCU with its important instruments and sections.

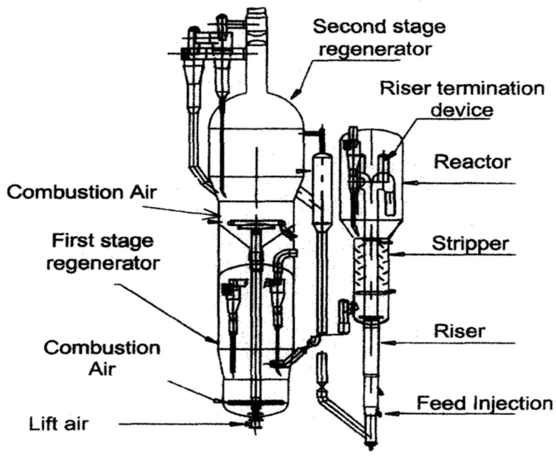

Fig. 1: Schematic diagram of a FCCU

Fuzzy Logic is a systematic mathematical formulation for investigating and characterizing processes with different levels of uncertainty. It is the best choice when a mathematical model for the process does not exist, or exists but is too complex to be evaluated fast enough for real time processing. In these situations, difficulties arise in using conventional control methods [3]. The FCCU popularity is mainly market driven, and this fact should also be considered in controller design because most of the times, the production of one or two products is demanded more seasonally [2]. The FCCU processes are notorious for being nonlinear, time invariant and full of uncertainties, which make them very difficult to model, simulate and control. For such processes, the conventional controllers (PID) become inefficient since they require good mathematical model of the plant; therefore, new methods and approaches are demanded [3]. Moreover, FCCUs continue to play a key role in any refinery as the primary conversion unit. For many refineries, they are the key to profitability. The successful operation of the process unit determines whether or not the refinery can remain competitive in today's market. FCCUs utilize a micro-spheroid Catalyst that fluidizes when properly aerated. The main purpose of the unit is to convert high-boiling petroleum fractions called Gasoil to high-value,

Manuscript received July 23, 2013; revised July 29, 2013.
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high-octane gasoline and heating Oil. Gasoil is the portion of crude Oil that boils in the range 650°F to 10508^{+o}F (330°C to 5508°C) and contains a diversified mixture of paraffin, naphthenes, aromatics and olefins [4]. In FCCU, feed Oil is contacted with re-circulating Catalyst and reacted in a riser tube. The feed Oil vaporizes and is cracked as it flows up the riser, thus forming lighter hydrocarbons (the gasoline fraction). Large amounts of Coke are formed as a by-product. The Coke deposits on the Catalyst and reduces its activity. The lighter hydrocarbon products are separated from the spent Catalyst in the Reactor. Steam is supplied to strip the volatile hydrocarbons from the Catalyst. The Catalyst is then returned to the regenerator where the Coke is burnt off in contact with air. This is usually done by partial or complete combustion. The regenerated Catalyst is then, re-circulated back to be mixed with the inlet feed Oil from the crude unit [5].

The selection of variables also plays a crucial role in the performance of Petrochemical plants like FCCUs. There are many discussions on proper selection of FCCU variables in Fuzzy optimization projects [6], [7]. However, the focus of this paper is on the key variables with which the process can be manipulated to achieve desirable results. These variables can either be categorized as Input-Output or Dependent-Independent ones. The input variables are Feed Rate, Specific Gravity, Catalyst Recirculation Rate, Air Flow Rate, Cumulative Feed Rate and Regenerator Temperature. The output variables are Riser Temperature, CO2/CO ratio, Coke deposited on the Catalyst, Feed (Gasoil) conversion Rate, Coke and LPG. Selection of proper variables can be tricky and may lead to quite different results. A detailed review on variable selection and its consequent outcomes in FCCUs has been already investigated [5].

II. Evolution of Fuzzy Logic in Fluidized Catalytic Cracking Units

Before the introduction of Fuzzy Logic, the investigations of scientists and researchers were limited to mathematical models, which had been exclusively developed for FCC plants [8], [9]. These models had different levels of precision. Others focused their research on the comparison of different models and their advantages and disadvantages over each other [10]. Due to the importance of FCCUs in industry and market, many scientists have approached this topic from different angles, e.g. stability, optimization, mathematical modeling and simulation. A complete literature on FCCU controllers and their continuous progress over the years is explored [2], [5]. Some significant works on the analysis and implementation of FCCUs with the focus on safe operation are also available [11], [12]. In addition, there are many researches on optimization and stabilization of FCC plants [13], [14], [15], [16].

An earlier work showed that Fuzzy model has better accuracy compared to statistical methods for the process identification [17]. Many researchers and scientists have already tried to implement the linear regression techniques and complex Kalman filtering approaches to enhance the accuracy [18], [19]. All the aforementioned methods suffer from the inability to model and control a real plant, which has a great deal of inherent nonlinearity, impreciseness and uncertainty [20], [21]. Thus, other new approaches such as neurofuzzy and genetic algorithms started to emerge [17], [22], [23], [24], [25], [26], [27]. Modern control techniques, such as parameter estimation, stochastic and optimal control, are used in model identification. However, some industrial processes are too complicated to be modeled or controlled by math-based algorithms because they are highly nonlinear and significantly uncertain with unknown or imprecise information [28]. Fuzzy Logic is an ideal tool for dealing with dynamic, nonlinear and imprecise models. It employs the linguistic rules to deal with mathematically vague processes and plants. These kinds of situations are widely present in industrial units like Petrochemical plants, nuclear plants and water treatment facilities.

For processes, which are known microscopically, hard control is clearly the preferable methodology. However, conventional control techniques have generally failed to solve industrial problems with poor mathematical models. Fuzzy Logic and artificial neural networks are two examples of soft computing, which have migrated into the realm of industrial control over the last two decades. Chronologically, Fuzzy control was the first and its application in the process industry has led to significant improvements in product quality, productivity and energy consumption. Currently, Fuzzy control is firmly established as one of the leading advanced control techniques in use. Today, the scientific trend is toward Fuzzy Logic and Neural networks [29]. The intelligent control becomes the center of interest when the system parameters can be manipulated to derive the results using familiar linguistic rules. The goal of this study is then to find the nonlinear relationship between input-output variables and define a solid optimization scheme to increase the efficiency by reducing the deposited Coke on the Catalyst and increasing the Gasoil conversion and LPG production.

III. Fuzzy Control: A Conceptual Review

Fuzzy Logic is a system that emulates the human expert decisions. Therefore, it is intuitively easy for humans to comprehend and apply in engineering and non-engineering applications. Fuzzy Logic results require no further elaboration or explanation because often times, the results are described in terms like cold, hot, small, big, fast, slow, which are easy for everyone to understand. To implement Fuzzy Logic, the knowledge and experience of an expert are necessary. The experience is written in a rule-based format, which is used for making database as well as Fuzzy rules. The more accurate the rules are, the more applicable the results will be. It is noteworthy to mention that these rules are approximate; which is exactly the same way a human's decisions are [2]. The human expert can be substituted by a combination of Fuzzy ruled based system (FRBS) and a block called de-fuzzifier. The sensory crisp data is then fed into the system where the physical values are represented or compressed into heuristic variables based on the appropriate membership functions. These linguistic variables then will be used in antecedent (IF-Then) part of statements and will be changed and revised to a crisp (numerical) output that represents an approximation to the actual output y(t) in defuzzification process. The key point of Fuzzy Logic is that

ISBN: 978-988-19253-1-2
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

it does not require the deep knowledge of the plant itself and how the processes are involved internally. This useful characteristic is not feasible with conventional controllers like PIDs [29] [30]. Fig. 2 depicts the main parts of a Fuzzy logic controller. Note that (1) the "rule-based system" holds the knowledge in the form of a set of rules of how to best control the system; (2) the inference mechanism evaluates which control rules are relevant to the current time and decides what the inputs to the plant should be accordingly; (3) the Fuzzification interface modifies the inputs so that they can be interpreted and compared to the rules in the rule-base; and (4) the defuzzification interface converts the conclusions reached by the inference mechanism into the inputs to the plant [30].

IV. Fuzzy Modeling of FCCU

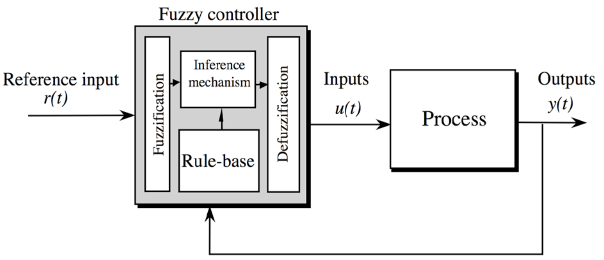

Fig.2: Fuzzy control system typical block diagram

A. Variable Selection: Input-Output parameters

The data in this study is gathered from the operation manual and other technical documentations of Abadan FCC refinery in 2004. Due to the lack of the mathematical model, rule based Fuzzy approach is employed. In order to have the plant modeled, the FCCU operating variables have been identified as input and output ones, which will correspond to independent and dependent variables, respectively. Table I shows 16 major variables in an FCCU process, including the manipulative and measured variables. The Fuzzy controller determines the behaviors of the variables and their relationships with each other via generating dynamic nonlinear graphs, known as surface graphs. Among all of the factors affecting FCCU and also based on their importance and level of consequence in the process, six input and six output variables are selected. In order to optimize the plant, measurement and manipulative variables are also identified. The Riser and Regenerator temperatures will be monitored all the time, and the Catalyst feed rate and airflow rate, as the manipulative variables, will be altered to adjust the parameters and achieve desired results.

B. Fuzzy logic controller design for FCCU

In order to process the input-output nonlinear relationship, six steps are considered in the creation of the rule based Fuzzy system [31]. These steps are as follows:

1. Identify the inputs and their ranges and name them.
2. Identify the outputs and their ranges and name them
3. Create Fuzzy membership function degrees of truth
4. Create the Rule base required for controller design
5. Assign the strength of rules and their interactions
6. Combine the rules and defuzzify the output

TABLE I
Input – Output Variables in Fuzzy logic controller

Input Variables	Output Variables
Regenerator Temperature (RET)	Coke as Bypass Product (Coke)
Specific Gravity Factor (SG)	Liquefied Petroleum (LPG)
Airflow to Regenerator (ATR)	Big Impact
Gasoil (Feed)	Gasoil Conversion Rate (GOCR)
Cumulative Feed Rate (CFR)	CO2/CO
Catalyst Recirculation Rate (CCR)	Riser Temperature RIT)
Manipulative Variable	**Measured Variables**
Airflow Rate	Riser Temperature
Recycled Catalyst Rate	Regenerator Gas Temperature

The data clustering for membership functions is also shown in Table II. For generating knowledge base and rules, knowledge of an experienced Process engineer and a Senior Instrumentation engineer working on the plant were gathered. The rules were configured using the operation manuals and other technical documents issued by the licensor.

TABLE II
Variables Clustering Ranges

Clustering Group	Equivalence
Low	Small Impact
Medium	Steady State
High	High Impact

TABLE III
Clustering ranges for Input variables

Input Variables	Low (L)	Medium (M)	High (H)
RET (°C)	0 – 610	575 – 645	630 – 670
SG (-)	0 – 0.660	0.452 – 0.796	0.668 – 0.878
ATR (m3/h)	0 – 29,873	27,001 – 47,209	39,451 – 60,167
Gasoil (m3/d)	0 – 1,980	1,770 – 2,151	1,967 – 2,250
CFR (m3/d)	0 – 2,260	2,011 – 2,450	2,289–2,650
CRR (t/min)	0 – 15.2	11.2 – 16.1	14.9–16.9

The initials of input and output variables and their corresponding ranges are shown in Tables III and IV, respectively. These ranges were used as the ranges for membership functions.

ISBN: 978-988-19253-1-2
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

TABLE IV
CLUSTERING RANGES FOR OUTPUT VARIABLES

Output Variables	Low (L)	Medium (M)	High (H)
Coke (wt.%)	0 – 4.2	3.4 - 7.5	5.2 – 9.1
LPG (wt.%)	0 – 18.5	14.3 – 21.8	19.5 – 30.9
DCC (-)	0 – 0.791	0.397 – 0.865	0.753 – 0.980
GOCR (wt.%)	0 – 76.8	44.9 – 93.8	79.3 – 98.16
CO2/CO (mol/mol)	0 – 1.8	0.9 – 3.9	2.2 – 6.2
RIT (C°)	0 - 479	404 – 520	505 – 528

C. Fuzzy Logic Rules

The list of the rules connecting the input variables to the output variables is shown below. These rules were implemented in Matlab Fuzzy rule editor to generate the inference and nonlinear surface model.

1-If (SG is H) then (LPG is M)(GOCR is H)
2-If (SG is H) then (Coke is H)(CO2/C0 is H)
3-If (SG is H) then (DCC is M)(RIT is L)
4-If (SG is L) then (CO2/C0 is L)
5-1f (SG is L) then (RIT is H)
6-If (ATR is H) then (Coke is H)
7-If (ATR is H) then (RIT is M)(CO2/C0 is M)
8-If (ATR is M) then (CO2/C0 is M)
9-If (ATR is M) then (DCC is L)
10-If (ATR is M) then (Coke is M)
11-If (ATR is L) then (CO2/C0 is L)
12-1f (ATR is L) then (DCC is M)
13-If (RET is H) then (RIT is M)(CO2/C0 is L)
14-If (RET is H) then (DCC is H)(LPG is M)(GOCR is L)
15-If (RET is H) then (Coke is M)(DCC is H)
16-If (RET is H) then (RIT is H)
17-1f (RET is M) then (Coke is M)(LPG is M)(GOCR is H)
18-If (RET is M) then (CO2/C0 is M)
19-1f (RET is M) then (Rh T is H)
20-If (RET is M) then (Coke is M)
21-If (RET is L) then (RIT is M)
22-1f (RET is L) then (DCC is L)
23-If (RET is L) then (CO2/C0 is L)
24-1f (RET is L) then (Coke is L)
25-If (RET is L) then (LPG is M)(RIT is L)(GOCR is L)
26-If (CFR is H) then (RIT is M)(GOCR is M)
27-If (CFR is H) then (DCC is L)(LPG is H)(RIT is M)(GOCR is H)
28-If (CFR is M) then (DCC is M)(LPG is M)(RIT is M)
29-If (CFR is L) then (DCC is M)(LPG is L)(GOCR is H)
30-If (CRR is H) then (Coke is M)(RIT is H)(GOCR is L)(CO2/C0 is H)
31-If (CRR is M) then (Coke is M)(GOCR is M)
32-If (CRR is L) then (Coke is L)(GOCR is M)
33-If (Gasoil is H) then (RIT is M)(GOCR is L)(CO2/C0 is L)
34-If (Gasoil is M) then (GOCR is M)
35-If (Gasoil is L) then (GOCR is H)

In Fuzzy control, there is an emphasis on using rules while in conventional control this level of emphasis is on ordinary differential equations. Using linguistic rules rather than the math-based system is more natural to human cognition. In Fuzzy rule, the rules are always true, but to different levels ranging from zero to one. The inference system first checks if the premises of the rules are valid for the current case. If the premises satisfied the requirements, those rules are selected. This step is also known as "Matching." The inference system makes the decisions afterwards.

Figs. 3 - 6 show four of the membership functions used in this research. In order to gain the optimum results, the center of the functions has been manipulated.

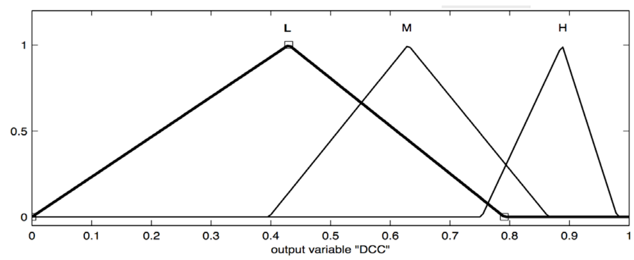

Fig. 3: DDC membership functions

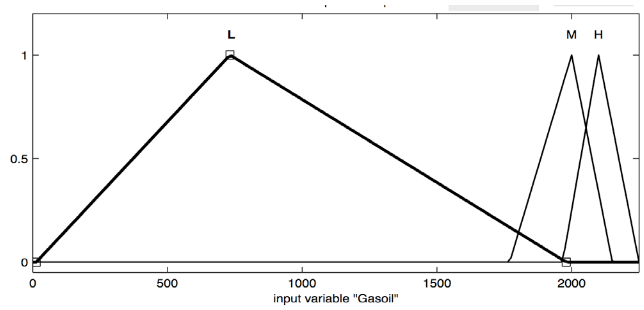

Fig. 4: Gasoil membership functions

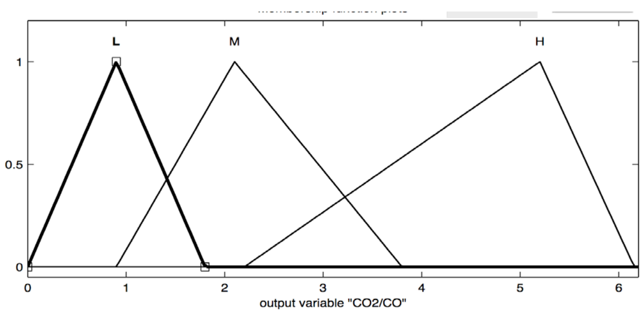

Fig. 5: CO2/CO membership function

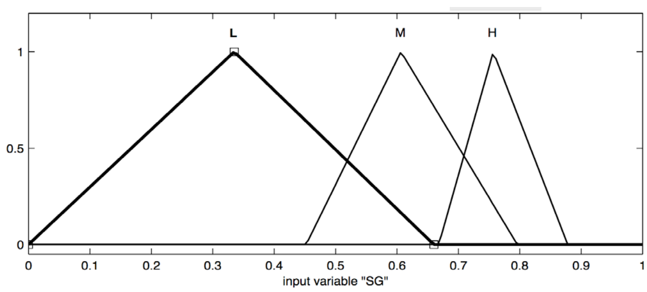

Fig.6: SG membership function

Another advantage of Fuzzy modeling is that once the whole system is modeled, selection of different variables and thus different modes can be easily evaluated without

ISBN: 978-988-19253-1-2
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

further manipulation of the plant or the controller.

D. *Defuzzification*

Defuzzification is the last step Fuzzy controller should do in order to produce a control signal, which will be fed into the plant via manipulating variables. The inference mechanism selects the most certain situation and produces the output accordingly. Defuzzification aims to produce a nonfuzzified control action that best represents the possibility distribution of the inferred Fuzzy decision [32].

Fuzzy surface provides very valuable information about the plant, including the correlation of the Input-Output variables, the speed the system reacts to the changes in the input and the direction of changes. These types of information enable engineers to analyze the plant in a completely new way, which is not feasible by conventional control methods.

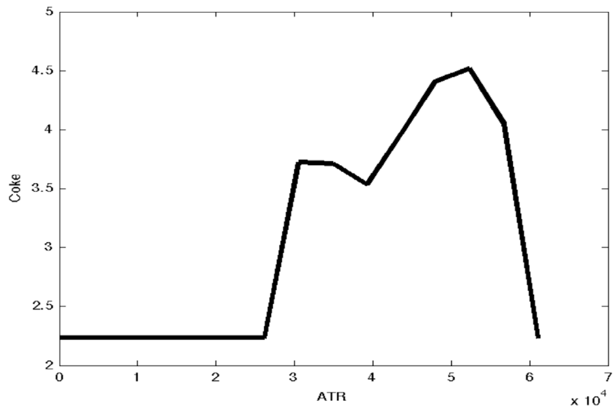

Fig. 7: Coke production according to ATR only

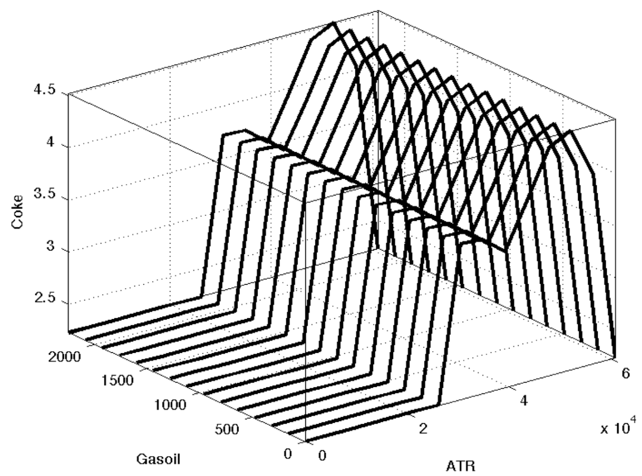

Fig. 8. : Coke production according to Gasoil and ATR

It is a very useful to have the ability to test many possible outcomes simultaneously without the need to derive the mathematical formulations in the system.

V. RESULTS

Conventional control has successfully provided the industry with satisfactory results with which many math-based problems can be addressed accurately. However, the inability of this type of control, along with its dependence to approximating the nonlinear and highly dynamic plants, have made the Fuzzy Logic a superior choice for control engineers dealing with nonlinear and dynamic cases. In Fuzzy control, Ordinary Differential Equations (ODEs) are

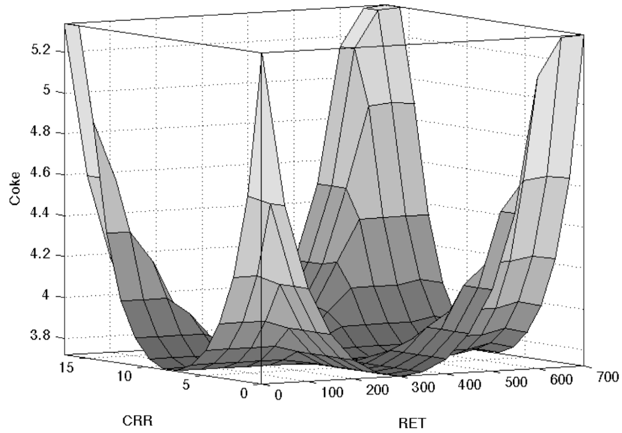

Fig. 9. : Coke Production according to CRR and RET

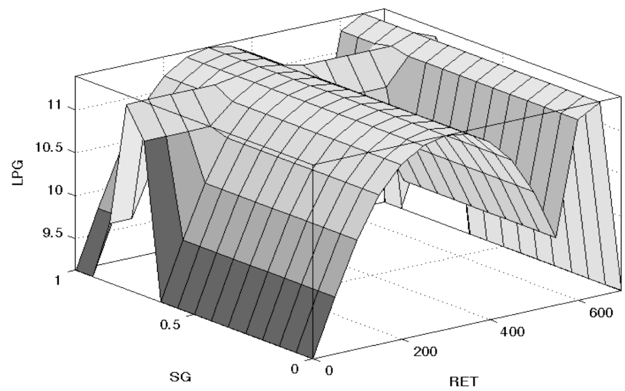

Fig. 10. : LPG production according to SG and RET

replaced with the skill of an expert in the field. In recent years, many scientists have focused on other aspects of Fuzzy Logic like learning through experience. The Neuro Fuzzy approach is now well established in the industry and seems to have a very promising future.

Through this research, the data was used in operation manuals and other technical documents to generate the necessary information for Fuzzy Logic modeling and controller design. This information was implemented in Matlab Fuzzy Logic Toolbox 2012b, and the results were demonstrated in Figs. 7 - 10. The Fuzzy Logic is exempted from the heavy mathematical formulations to produce the output. However, the expertise and knowledge of an experienced operator is essential. The plant examined in this paper, used to be controlled and monitored via Yokogawa Distributed Control System (DCS) and the rules had been implemented into the system by customized programming, which required manual manipulation and intervention when modes are switched or at the time of maintenance and overhauls. The data generated in this paper had an acceptable precision with those obtained in plant operation. The data was extracted in the year 2004 and may be different from operating conditions at the time of writing this paper. The Fuzzy controller was successfully modeled and could produce decent results. Some of the results found in this paper were in good compliance with actual ones in operation; others like CRR and CFR required more tuning to be acceptable.

Once the Fuzzy modeling of the plant is complete, many useful insights and conclusions can be made. For instance, in Fig. 7, the Coke production pattern according to ATR is demonstrated. As depicted, the Coke production follows a linear trend from 26,000 (wt.%) to 30,000 (wt.%) according to the input variable ATR, and consequently, it can be modeled via a linear mathematical formula. In addition, upon the increment of ATR variable from 30,000 (m^3/h) to 40,000 (m^3/h), a linear decrease in Coke production is observed. The maximum of Coke production occurs at ATR value of 54,000. This pattern recognition also enables engineers to implement the numerical optimization techniques to enhance the plant productivity. Another noteworthy advantage of the Fuzzy Logic over conventional control is observed in 3D result of Fig. 9. As it is shown, the 3D graph near the origin is almost similar to that generated via a PD controller. Therefore, a Fuzzy Controller can produce the results of a PID controller while the conventional controllers are not the proper means to address the nonlinear and uncertain industrial models like FCCUs. Fig. 8 and Fig. 10 are also two other examples of Fuzzy modeling in this paper, and a similar analysis can be made.

VI. Conclusion

Fuzzy Logic approach proved to be capable of generating satisfactory results while facing nonlinear and dynamic situations. It was also the prefect tool to address the nonlinearity and uncertainty inherent in FCCUs and Petrochemical plants in general. A Fuzzy controller was designed to address the nonlinearity and uncertainty of the FCC plant with acceptable performance. Generating more accurate rules, increasing the number of rules and using numerical optimization techniques can further refine the results. In addition, modern control techniques like Neuro Fuzzy and Artificial Intelligence can be employed to tailor the outcome further.

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ISBN: 978-988-19253-1-2
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)