

The Comparison of Artificial Intelligence and Traditional Approaches In FCCU Modeling

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FCCU (Fluid Catalytic Cracking Unit) is a part of oil refinery production process whereby valuable products such as gasoline, LPG (Liquid Petroleum Gas), diesel are manufactured in a short period of time. The objective of this paper is to find the most robust model by comparing the models of FCCU that are developed using different methodologies. The models of FCCU are developed by using Artificial Neural Network (ANN), Fuzzy Logic, Neuro-Fuzzy, and traditional methodology. In this paper, the criteria used for measuring the performance of different models is root mean squared error (RMSE). The models are applied to the real data obtained from TUPRAS (Turkish Petroleum Refineries Corporation)-FCCU. Kurihara (1967) model is used as the traditional model for comparing with intelligence modeling techniques. Finally, the Fuzzy Neural Network (FNN) model was found as the model with the minimum RMSE. *Qwicknet 2.23*, *MATLAB 6.5*, and *Neuro-solutions 4.1* softwares have been used for the construction of ANN, fuzzy, and neuro-fuzzy models, respectively.

Significance: In this paper, three intelligent modeling techniques are compared to not only with each other but also with traditional approach. The model that is developed using fuzzy neural network can be applicable to fluid catalytic cracking unit in an oil refinery to maximize the gasoline yield and it is shown to be better than the other modeling techniques.

Keywords: Fluid catalytic cracking, fuzzy modeling, fuzzy neural network, artificial neural network

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1. INTRODUCTION

FCCU is the heart of refinery since it produces a significant added value for the national economy. A small improvement in FCC process can result in significant gain. Depending on the particular unit, such a system can result in a 0.05\$ to 0.20 \$/bbl improvement from advanced control, a 0.20\$ to 0.80 \$/bbl from on-line optimization (Lin, 1993). Most refiners operating FCC units try to maximize gasoline yield. Other processing objectives such as maximizing distillate yield or liquefied petroleum gas yield are also becoming more common. Maximizing gasoline yield, however, remains as the most-common FCC processing objective. The function of FCCU is to convert heavy hydrocarbon petroleum fractions into more usable products such as gasoline, middle distillates, and light olefins. FCC is a complex system that made up of heat balance, pressure balance, and chemical balance. The complexity of FCC arises from the reaction kinetics, catalysts hydrodynamics, coke combustion on catalysts, process economics, operating constraints, and interactions of the process variables that are dominated by the heat balances between reactor and regenerator. The changes in one operating variable always result in equilibrating changes in other variables, sometimes reversing and sometimes adding to the expected changes because of its dynamic structure. In theory, if a good overall nonlinear model is available, it is possible to use it to directly control all manipulated (control) variables, both slow and fast, to monitor the system in the desired operating space. Before undertaking the study of the dynamic and steady state control of any complex system such as FCC system, one needs an adequate model. Such systems have two main aspects in common; a) In general, they are nonlinear and their models are seldom known accurately, b) The number of variables that need to be controlled is much larger than the number of controllable variables available for the control.

Any control or optimization study of the FCCU requires a process model, which captures the major effects and interactions taking place in the unit. The effects of most changes are nonlinear. *Robustness* is the ability of a system to maintain its functionality across a wide range of operational conditions. Robustness indicates system performance. A common goal that designers and engineers of complex systems strive for is to obtain a robust and functional model to run

the system as productive. System modeling and identification are the basic issue in the design of a control system. Since FCCU is a complex system, mathematical models are either too complicated for optimization or too simple for process representation. System modeling and control by use of intelligent systems have been rapidly increasing in the last decades (meziane, et.al., 2000). While system modeling based on ANNs is like a black box approach, fuzzy logic systems are knowledge-based systems consisting of linguistic If-then rules that can be constructed using the knowledge of experts. Especially, when we deal with a system which involves human interventions, the conventional modeling techniques may have difficulty in realizing the system. But, fuzzy modeling is able to combine numerical and symbolic processing into one framework. Firstly, the linguistic if-then rules can realize qualitative knowledge, human concepts, and human interventions. Secondly, fuzzy systems are universal approximators of highly nonlinear mappings. Therefore, system modeling by fuzzy logic is a quantitative as well as a qualitative approach. Intelligent control has been applied with considerable success in the process industry. Examples can be found in the petrochemical, cement, paper, fertilizer, and metal industries. The use of intelligent control techniques for modeling FCCU can overcome some weaknesses and resolve some of the problems (King, 2005). This study is applied to the TUPRAS-izmit Refinery that is the largest oil refinery in Turkey. The mathematical model describes the UOP FCC System adopted by the TUPRAS in its industrial unit.

2. LITERATURE REVIEW

FCCU in the petroleum refinery consists of reactor, regenerator, and fractionator. There are many mathematical models for the FCCU in the literature. Some of them use extensively regenerator and reactor models coupled. Some authors have only regenerator models. Others have reactor or cracking models. Optimal control algorithm of FCC process was used for the first time by Kurihara (1967). Many authors such as Mc Farlane, did not use the fractionator unit in their models as a part of FCC process and also affecting it to avoid complication (Sundaralingam, 2001). Mc Farlane's model (1993) explains computing the complex pressure balance and catalyst circulation rate for integrated reactor and regenerator. It doesn't predict feed conversion. The Lee-Grooves (1985) model uses a plug flow reactor (PFR) model for the reactor riser and a continuous stirred tank reactor model for the regenerator with the three lump model of Weekman and Nace (1970) to describe the cracking reactions. The main problem of the model is a lack of detailed kinetics for the combustion of CO and CO₂. The model by Arbel et al. (1995) uses a PFR model for the reactor with the ten lump model of Jacob et al. (1976) to describe the cracking kinetics. Khandelakar and Riggs (1995) combined the Amoco FCC model with the model of Lee and Grooves (1985). Han and Chung (2001) developed a detailed model of a modern riser-type FCC unit that consists of the reactor, regenerator, and catalyst transport lines with slide valves. The model used by Arbel et al. (1995) suggests a new model for FCCU based on a more detailed kinetic description of the kinetics in both the reactor and the regenerator. Secchi et al. (2001) presented a theoretical dynamic regenerator – riser model for FCC to predict operating variables. Ali and Rohani (1997) developed dynamic model for FCC unit to describe the dynamic behavior of both the riser and the regenerator reactors and their interactions. The cracking reactions are simulated by the four-lumped kinetic model. Yescas et.al (1998) explains a theoretic method by using a non-linear model for pre-analysis of controllability of a FCCU. Ramirez et al. (1996) develops an adaptive model-based strategy to control the temperature of reactor-regenerator system. Ali and Elnashaie (1997) had some studies to control a non-linear model predictive of Industrial type IV for maximum gasoline productivity. Studies related to FCCU on intelligence modeling such as artificial neural networks, fuzzy and neuro-fuzzy have been achieved and focused for the last ten years. Fuzzy modeling and fuzzy expert-optimization control in FCCU by using fuzzy relation equations was applied in a Chinese petroleum refinery by Lu et al. (1997). Zeydan (1999) uses a fuzzy modeling and control approach in a Turkish Refinery including fractionator subsystem in FCCU. Alaradi and Rohani's paper (2002) presents identification and control of a riser-type FCC unit using neural networks. Taskin et al. (2006) uses a fuzzy modeling and control approach in a Turkish Refinery to maximize the outputs. Azeem, et al. (2007) presented a generalized fuzzy model and identification of FCCU for multi input-single output variables. The structure identification and the parameter estimation were carried out using hybrid learning approach comprising modified mountain clustering and gradient descent learning with least square estimation for the identification of a fuzzy model. Zanin et al.'s paper (2001) focuses on the modeling of the practical implementation of an optimizing controller in a FCC unit. Michalopoulos et.al. (2001) makes a modelling study of an industrial fluid catalytic cracking unit using neural networks. Some basic studies that provide significant contribution on traditional modeling, control and optimization related to FCC are classified into the table 1.

Table 1. Studies related to basic FCCU modelling, controlling and optimization

Reactor Models	Weekman and Nace (1970), Paraskos et al. (1976), Jacob et al. (1976), Shah et al. (1977) Takatsuka et al. (1987), Lee et al. (1989), Larocca et al. (1990), Shnaider and Shnaider (1990), Theologos and Markatos (1993), Farag et al. (1993), Theologos et al. (1997)
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Regenerat or Models	Ford et al. (1976), Errazu et al.(1979), de-Lasa et al. (1981), Guigon and Large(1984), Krishna and Parkin (1985), Lee and Cheng (1989), Faltsi-Saravelou et al. (1991-a,b)
Reactor-Regenerat or Models	Luyben and Lamb (1963), Kurihara (1967), Kunii and Levenspiel (1969), Iscol (1970), Lee and Kugelman (1973), Seko et al. (1978-1982), Errazu at al. (1979), Elnashaie and Elhennawi (1979), Krishna and Parkin (1985), Lee and Groves (1985), Mcgreavy and Isles-Smith (1986), Bozicevic (1987), Zhao and Lu (1988), Elshishini and Elnashaie (1990), Felipe and Richard (1991), Arandes and de Lasa (1992), Mc Farlane et al. (1993), Zheng (1994), Arbel et al. (1995), Elnashaie et al. (1995), Ellis et al. (1998), Han, Chung, and Riggs (2000), Han and Chung (2001), Dave and Saraf (2003)

3. LOCATION AND DESCRIPTION OF THE FCCU IN AN OIL REFINERY

Figure 1 illustrates a schematic drawing of a modern oil refinery. Here the feed to the FCCU consists of vacuum gas oil (VGO) from the vacuum unit and heavy atmospheric gas oil from the atmospheric (Atmos Unit) crude distillation unit. The heavy atmospheric gas oil can also be directed to the hydrocracker or it can be split with part going to the FCCU and part to the hydrocracker. Coker Gas oil (CGO) can be charged directly to the FCCU when the hydrocracker is down. Feedstock is converted to various products in the reactor of the FCCU. These products undergo additional processing and separation in the main fractionator and other vessels downstream of the FCCU reactor. The catalytically cracked gasoline and lighter products are processed further in the Gas Concentration Plant (Gas Con). The dry gas from the Gas Con is directed to the refinery fuel gas system after sulfur removal. LPG is sent to storage for sale as fuel or for use in adjusting the vapor pressure of gasoline. Two units were lumped into Ether unit. LCO (Light Cycle Oil) from the cat cracker can be sent directly to storage for blending into distillate fuel such as No.2 or diesel fuel. LCO stream can also be directed to the hydrocracker for conversion into lighter products or it can be split as feed to the hydrocracker and as distillate product to storage. The system is totally adiabatic. Most modern versions of the FCC are equipped with a feed preheater that allows the feed temperature to be raised to a specified value. All FCC's are autothermic and require heating to start up the system. Nonlinear systems like FCC can have, in addition to multiple steady states, input multiplicities. (Meyers, 1996)

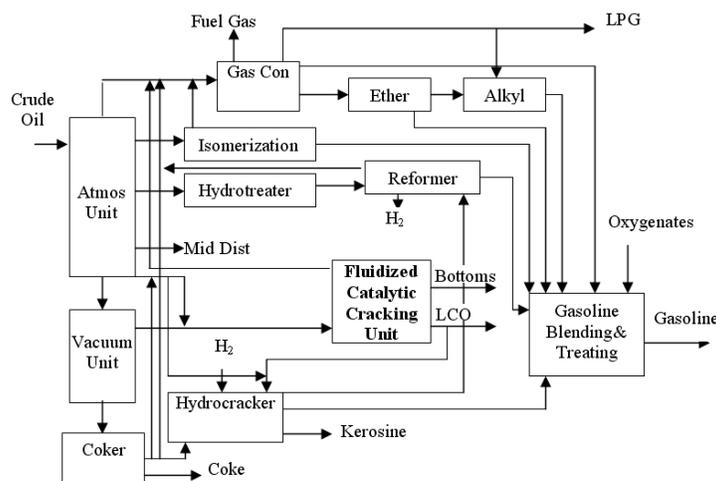


Figure 1. Location of the FCCU in the oil refinery.

Figure 2 illustrates the schematic drawing of a FCCU. Fresh feed preheated in the furnace is mixed with hot slurry recycle from the bottom of the main fractionator and injected into the reactor riser where it mixes with the hot catalyst and is vaporized. In the reactor riser, the high molecular weight feed is partly cracked to the low molecular weight products. The hot catalyst provides the heat for this endothermic cracking reaction. During cracking, coke (Carbon and 5-10 % hydrogen) is deposited on the catalyst, reducing the catalyst activity. Product gas from the reactor goes to the main fractionator for heavy recovery and separation into various product streams. Wet gas (C4 and lighter) from the main fractionator is compressed for further separation in downstream fractionators. The entrained catalyst is separated from the product gas in the cyclones at the top of the reactor and returned to the stripping section of the reactor where steam is injected to strip off the entrained hydrocarbon from the catalyst. The hydrogen in the coke comes from the hydrocarbons

entrained in the catalyst since the stripping is never completely successful. The separation area is the main fractionator and gas plant. The wet gas compressor belongs to the separation area, but sometimes it is considered to be in the reaction because it often limits conversion in the reactor. A unique feature of the FCC reactor is the behaviour of the catalyst. The catalyst loses its activity very rapidly (within seconds) due to coking. This loss of activity can be recovered by combusting the coke in the regenerator. The catalyst also loses activity more slowly but permanently due to steaming and exposure to higher temperatures. (Arbel et. al, 1995)

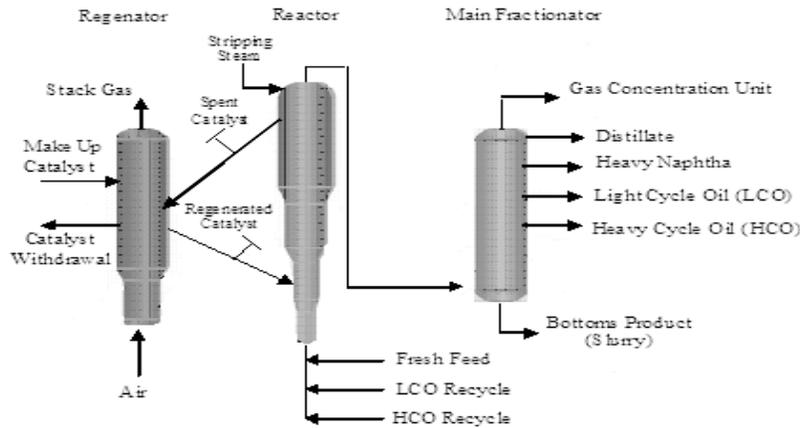


Figure 2. Schematic diagram of FCCU.

4. PROBLEM FORMULATION

FCCU operating variables have been termed independent and dependent variables and all these variables are directly controlled usually with a control meter. Figure 3 lists the major variables in a FCCU. Dependent operating variables are those that change as a result of a change in an independent variable. Below are the definitions of the major independent operating variables used for modeling the FCCU:

1. Reactor Temperature: The temperature of the catalyst-oil reaction mixture in the reactor.
2. Fresh Feed Rate: The bbls/day of non-catalytically cracked feed that are charged to the cat cracker.
3. Recycle Rate: The bbls/day of cat cracked product that are returned to the reactor for further cracking. The products normally recycled are those heavier than light cycle oil although light cycle oil is sometimes recycled.
4. Feed (preheat) temperature: The temperature of the feed (including recycle) to the cat cracker.
5. Air to Regenerator: The air rate, usually given in SCFM (standard cubic feet per minute), required to support the combustion of the coke deposit on the catalyst in order to remove the coke and thereby regenerate the catalyst.

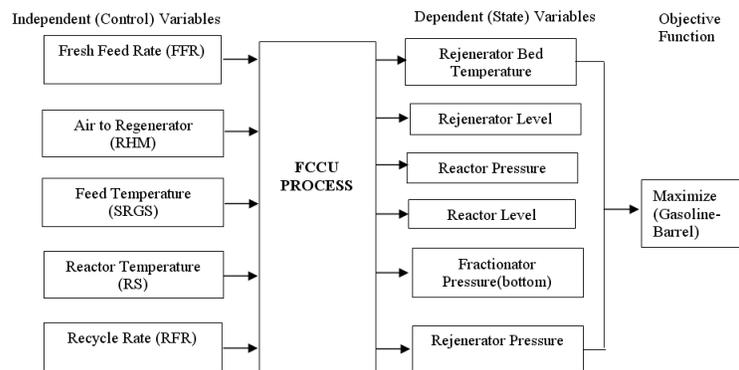


Figure 3. Major variables in the FCCU.

In TUPRAS-FCCU, the main objective for productivity criterion is the octane-barrel amount. The main aim of the refinery is to maximize the octane-barrel amount. The equation for the octane-barrel amount is given in (1).

$$\text{Octane-Barrel Amount} = (\text{Corrected Gasoline}) * (\text{The Amount of Octane}) / 0.159 \quad \dots(1)$$

Not only gas oil conversion but also the amount of octane must be high to get much more number of octane-barrel. As a matter of fact, while octane emphasizes on quality of gasoline, barrel shows amount of it. The productivity of FCCU is measured depending on this criterion so the octane-barrel amount is assigned as the dependent variable in the model of the FCCU of TUPRAS. A sample fluid catalytic cracking unit summary report of TUPRAS refinery is given in appendix D.

5. SYSTEM MODELING APPROACH WITH FUZZY LOGIC

The process of fuzzy modeling can be illustrated as the flowchart in Figure 4.

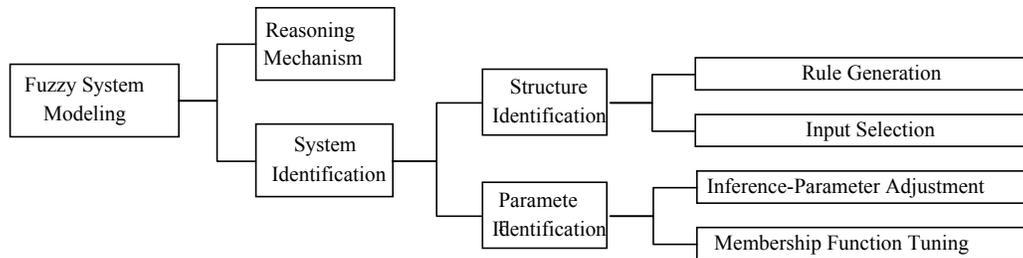


Figure 4. Flow chart of fuzzy system modeling.

The system identification is applied to the system modeling by Emami et al (1996-b). The fuzzy relational model can be represented as follows;

$$\begin{aligned}
 Y_1(k) &= X_1(k) \circ X_2(k) \circ \dots \circ X_n(k) \circ R_1 \\
 &\dots \\
 Y_m(k) &= X_1(k) \circ X_2(k) \circ \dots \circ X_n(k) \circ R_m
 \end{aligned} \tag{2}$$

where

- {X_i(k), i = 1, ..., n} fuzzy variables of system inputs;
- {Y_j(k), j = 1, ..., m} fuzzy variables of system outputs;
- {R_j, j = 1, ..., m} fuzzy relations between system fuzzy inputs and outputs;
- symbol o fuzzy composition operator.

On account of above statements, the FCCU of TUPRAS can be defined with fuzzy modeling as:

- C = F(X₁, X₂, X₃, X₄, X₅)
- F(·) = a fuzzy operator describing the fuzzy rule base
- C = Octane-Barrel Amount of Gasoline (OVM)
- X₁ = Fresh Feed Rate (FR)
- X₂ = Air to Regenerator (RHM)
- X₃ = Feed Temperature (SRGS)
- X₄ = Reactor Temperature (RS)
- X₅ = Recycle Rate (RFR)

therefore,

$$Y_j(k) = X_1(k) \circ X_2(k) \circ X_3(k) \circ X_4(k) \circ X_5(k) \circ R_j, \quad j = 1, \dots, c \text{ (c: the number of clusters)} \tag{3}$$

By using NCSS (Number Cruncher Statistical System) software program, the parameters in table 2 were identified entered for finding the number of cluster and intervals of selected variables. The number of cluster was obtained based on output variable. Generally, most users use the Euclidian distance method. Scaling the data is important so that all values are in comparable units. The maximum number of iterations are allowed during the iteration procedure. Fuzzifier constant is the exponent of the membership in the objective function that is being minimized. Normally, this value is set to two. Stopping rule for the algorithm is the minimum change. Minimum number of clusters is 2 and maximum number of clusters is 30.

After making the analysis of fuzzy clustering, the following table result was found. As seen in table 3, the best cluster number is 21. One of the most difficult tasks in cluster analysis is to choose the appropriate number of clusters. Average silhouette is used to aid in the search for the appropriate number of clusters by selecting the number of cluster that maximizes this value. The value should be positive and be greater than 0.5. The fuzzy algorithm used by this program is applied according to Kaufman methodology (<http://www.ncss.com>)

Table 2. Necessary parameters

Distance method	Euclidean	Minimum change	0.0000001
Scaling method	Standard deviation	Minimum clusters	2
Max. iterations	15	Maximum clusters	30
Fuzzifier constant	2		

Table 3. The Number of cluster

Number of Clusters	Average Silhouette	Number of Clusters	Average Silhouette	Number of Clusters	Average Silhouette
2	0,55	12	0,49	22	0,48
3	0,56	13	0,48	23	0,50
4	0,50	14	0,52	24	0,52
5	0,50	15	0,53	25	0,54
6	0,52	16	0,47	26	0,57
7	0,50	17	0,51	27	-0,98
8	0,51	18	0,57	28	-0,98
9	0,46	19	0,53	29	0,43
10	0,46	20	0,58	30	0,42
11	0,49	21	0,60		

For making a validation test (sensitivity analysis) of whether the number of cluster found is true or not, one by one in terms of rules, data set of the Refinery is trained and tested in MATLAB 6.5 software. Minimum difference (Real system output – Fuzzy model output) was found as 21 after trial and error. For example, as known, 21 cluster was found as the best cluster after making fuzzy clustering in NCSS software. For 21 cluster and 21 rules, according to the difference (absolute value of deviation) in table 4, the best suitable cluster is seen as 21 cluster.

Table 4. Validation test (Sensitivity analysis)

Number of Cluster and Rules	Difference	Number of Cluster and Rules	Difference	Number of Cluster and Rules	Difference
3	559785	10	547653	17	442651
4	624421	11	504861	18	487651
5	503653	12	514861	19	516651
6	527421	13	542860	20	485651
7	479031	14	650551	21	418651
8	526653	15	557419		
9	542653	16	457443		

In MATLAB software, fuzzy logic parameters have been used in table 5 as follows;

Table 5. FIS input parameters

And Method: Min.	Aggregation: Max.	Implication: Min.	Or Method: Max.	Defuzzification: Centroid
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The most commonly used defuzzification methods are the center of gravity (COG) and the centroid defuzzifier in spite of being used different types of defuzzification methods (Drienkov, et. al., 1996). The centroid defuzzifier method is used here. Mamdani's fuzzy inference method is the most commonly seen fuzzy methodology. Mamdani's method was among the first control systems built using fuzzy set theory.

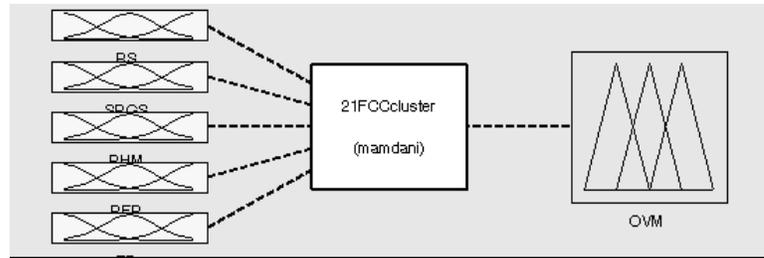


Figure 5. Fuzzy inference system (FIS) editor screen (inputs and output of the FCCU)

Mamdani-type inference expects the output membership functions to be fuzzy sets. After the aggregation process, there is a fuzzy set for each output variable that needs defuzzification. It's possible, and in many cases much more efficient, to use a single spike as the output membership function rather than a distributed fuzzy set. This is sometimes known as a singleton output membership function. It enhances the efficiency of the defuzzification process because it greatly simplifies the computation required by the more general Mamdani method, which finds the centroid of a two-dimensional function. More information can be found in MATLAB guide of the software. After training the data set of refinery, rules table was found as in table 6. For example,

If Reactor Temperature ($X_4=RS$) = 530 ($^{\circ}C$) and Feed Temperature ($X_3=SRGS$) = 272 ($^{\circ}C$) and Air to Regenerator ($X_2=RHM$) = 49400 ($m^3/hour$) and Fresh Feed Rate ($X_1=FR$) = 1880 ($tons/day$) and Recycle Rate ($X_5=RFR$) = 157 ($tons/day$) then octane-barrel amount of gasoline ($C=OVM$) = 575000 (Octane-Barrels)

Table 6. Rule table for FCCU of TUPRAS

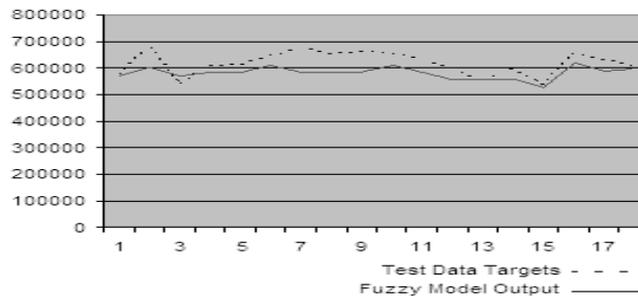
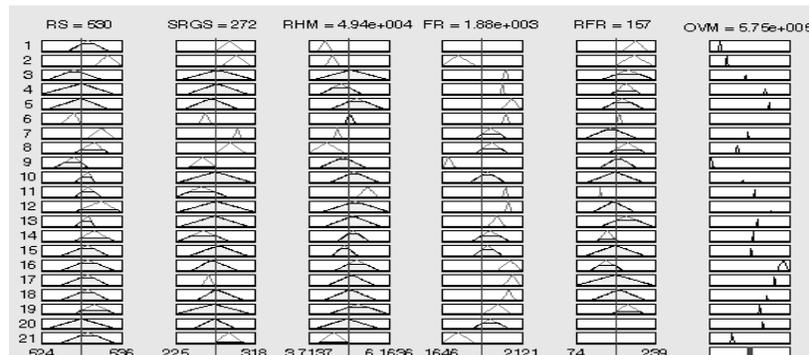


Figure 6. Testing results of fuzzy modeling for FCCU of TUPRAS.

There are 5 inputs and one output variable in the system. It is known that modeling and inference is more straightforward for the *MISO* (Multi Input-Single Output) fuzzy systems. The system identification is applied for fuzzy modeling. 98 training and 18 testing data are used to train and test the system during modeling process, respectively. After making fuzzy clustering using the *NCSS* software, 21 clusters (21 rules) are found. The rules are generated in the *MATLAB Fuzzy Toolbox*. Figure 6 illustrate the testing results of the fuzzy model of TUPRAS-FCCU. The RMSE for the testing data is calculated as 4.50E+04.

6. SYSTEM MODELING APPROACH WITH ANN

For the ANN model of TUPRAS-FCCU, a back-propagation neural network with one hidden layer is used. The input variables to the network are *Fresh Feed Rate*, *Air to Regenerator*, *Feed Temperature*, *Reactor Temperature*, and *Recycle Rate*. The output variable of the network is *Octane-Barrel Amount of Gasoline*. 98 training patterns and 18 testing patterns are used to train and test the network respectively. The parameters used for neural network modeling is as follows. The detailed description and information about the structure of Artificial Neural Network (ANN) is given in appendix B.

Table 7. The performance criteria used for neural network

Training properties	Stopping criteria	Training algorithm	Activation function
learning rate:0.1	epochs:100000	network topology: online backpropagation	input: logistic
momentum:0	Average RMSE (Root Mean Square Error): 0.01	hidden layers: 1	output: logistic
input noise:0	Max RMSE: 0.01	input hidden 1: 5	
weight decay:0	Max error:0.01		
error margin:0.1	percent correct:100		
pattern clipping:1			

All performance criteria in the Qwiknet software were tried time and again. The best results was obtained according to conditions in table 7. *Qwiknet* results after testing are given in Figure 7. The RMSE for the testing data is calculated as 3.90E+04.

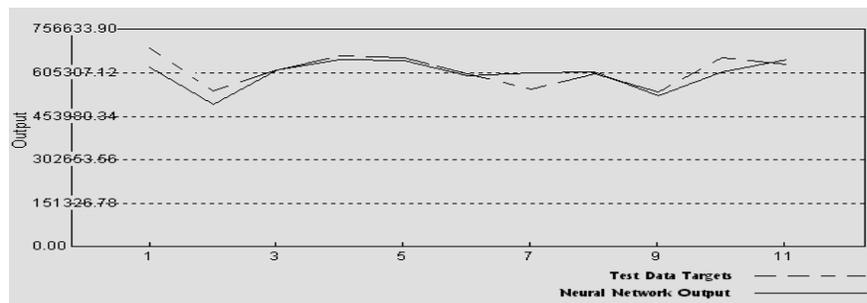


Figure 7. Testing results of neural network modeling for FCCU of TUPRAS

7. SYSTEM MODELING APPROACH WITH FNN

CANFIS(Co-active Neuro-Fuzzy Inference System) model integrates adaptable fuzzy inputs with a modular neural network to rapidly and accurately approximate complex functions. Fuzzy inference systems are also available as they combine the explanatory nature of rules (membership functions) with the power of “black box” neural networks. For the FNN model of TUPRAS-FCCU a back-propagation fuzzy neural network is used. The input variables to the network are *Fresh Feed Rate*, *Air to Regenerator*, *Feed Temperature*, *Reactor Temperature*, and *Recycle Rate*. The output variable of the network is *Octane-barrel Amount of Gasoline*. 98 training patterns and 11 testing patterns are used to train and test the network respectively. The parameters used for evaluating the system are selected as in table 8. After being tried all performance criteria by trial and error in the Neuro solutions software, the best conditions as seen in table 8 was obtained. Figure 10 illustrates testing results of FNN model of TUPRAS-FCCU. The RMSE for the testing data is found as 3.51E+04.

Table 8. The performance criteria used for FNN

Membership function: Bell	Learning rule: Quickprop	Max. epochs: 100000
Fuzzy model: TSK	Step size: 1	Termination: MSE Threshold: 0.01
Transfer function: Linear axon	Momentum: 0	Hidden layers: 1

Detailed description about the fuzzy neural network is presented in appendix C.

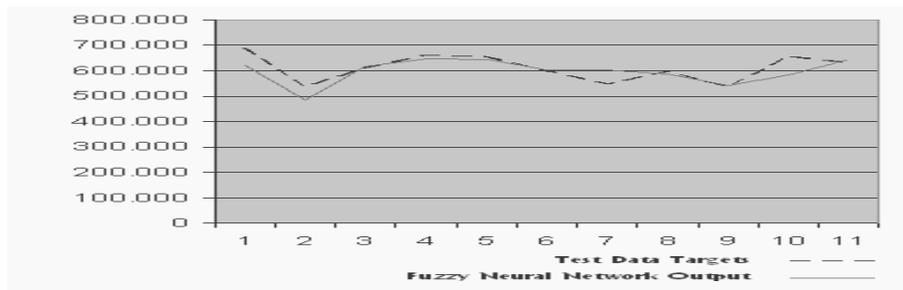


Figure 8. Testing results of FNN model.

8. SYSTEM MODELING APPROACH WITH TRADITIONAL METHODOLOGY

Kurihara (1967) model is used as the traditional model. To be able to find the Octane-Barrel amount, Y_{gl} equation in the yield equation of Kurihara (1967) is used. The yield model is over-simplified but is satisfactory for evaluating the system. $F_{gl}=1$ and $I_{gl}=0.9$ are taken among kinetic unit fitting parameters in steady-state situation. C_{tf} with every moment from FCCU summary report is obtained. Afterwards, Octane-Barrel amount is calculated according to Kurihara model. Detailed equations are given in appendix A. The results are shown in Fig. 11. The RMSE for the testing data is calculated as $9.25E+04$.

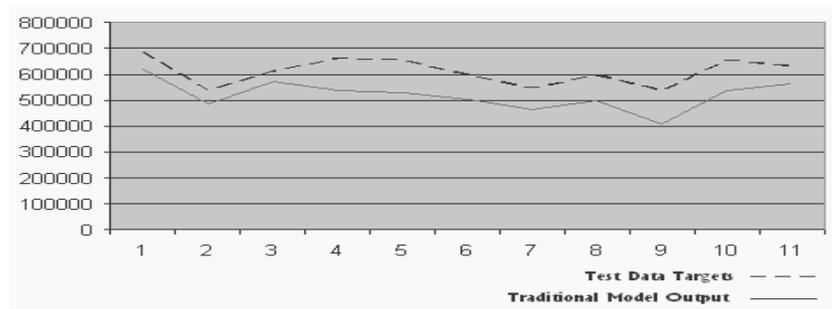


Figure 9. Traditional model results.

9. CONCLUDING REMARKS

This study provides an important added value with a huge literature review for academicians and practitioners studying in the area of FCC. In this paper, the most appropriate model was tried to be found and identified for FCCU comparing with Fuzzy, ANN, FNN and traditional techniques by looking at RMSE (Root Mean Square Error) values for the testing data. For all techniques, the actual values are utilized in calculating the RMSE values. The model obtained after training in the intelligent models are compared with testing values. At the end of modeling, according to the RMSE values, all models obtained from intelligent and traditional techniques are compared with each other. Thus, RMSE is the same in all cases evaluated. During fuzzy clustering, the most efficient control rules dependent on given data set of the TUPRAS-FCCU are generated by the help of fuzzy cluster means algorithm in NCSS software. Three intelligent modeling techniques are compared to not only with each other but also with traditional approach. The model that is developed using fuzzy neural network can be applicable to fluid catalytic cracking unit in an oil refinery to maximize the gasoline yield and it is shown to be better than the other modeling techniques according to the RMSE values of the models. All parameters in the Neuro solutions and qwiknet Softwares was tried to find out the best results by trial and error. According to the data set obtained from TUPRAS oil refinery, all analysis was performed. This study should be performed for other industrial systems to indicate the best modeling technique. As seen in table 9, the FNN model is the most robust process model. That is, FNN model has the best performance (robustness) compared to the other models as it has the smallest RMSE value. Kurihara's model has the highest RMSE value if compared to the other intelligent models. Here, only Kurihara's model was used and tested. Of course, the other traditional models should be tested for the future attempts. In this study, this is a proof that intelligent techniques are superior to the traditional techniques to the modeling non-linear systems as told in the literature.

This study can be used as a basis for the control and optimization of FCCU. The continuation of this study is planning to calculate the net profit to be obtained from the system with the process control and optimization based on the FNN model.

Table 9. RMSE values of Fuzzy, ANN, FNN and Traditional models of the TUPRAS-FCCU

Models	RMSE
Fuzzy	4.50E+04
ANN	3.90E+04
FNN	3.51E+04
Kurihara (1967)	9.25E+04

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APPENDIX A - TRADITIONAL MODELLING EQUATIONS

Rate Equations

$$R_{oc} = 1.75 D_{tf} R_{tf} C_{tf}$$

$$C_{tf}/(1-C_{tf}) = K_{cr} P_{ra} H_{ra} / R_{tf}$$

$$K_{cr} = k_{cr} / (C_{cat} C_{cr}) \exp\{-\Delta E_{cr} / R(T_{ra} + 460)\}$$

$$R_{cf} = K_{cc} P_{ra} H_{ra}$$

$$K_{cc} = k_{cc} / (C_{cat} C_{rc}) \exp\{\Delta E_{cc} / R(T_{ra} + 460)\}$$

$$R_{cb} = (R_{ai} / C_1)(2I - O_{fg}) / 100$$

$$O_{fg} = 2 \exp\{-P_{rg} H_{rg} / [R_{ai}(1/K_{od} + 100/K_{or} C_{rc})]\}$$

$$K_{od} = C_2 R_{2ai}$$

$$K_{or} = C_3 \exp\{(\Delta E_{or} / R)[1/1560 - 1/(T_{rg} + 460)]\}$$

Yield Equations

$$Y_{gl} = F_{gl} / (1 - I_{gl}) [(1 - C_{tf}) I_{gl} - (1 - C_{tf})]$$

$$Y_{co} = 1 - C_{tf}$$

$$Y_{ck} = 0.571 R_{cf} / R_{tf} D_{tf}$$

$$Y_{gs} = 1 - Y_{gl} D_{gl} / D_{tf} - Y_{co} D_{co} / D_{tf} - Y_{ck}$$

Table 10. Symbols of Equations

R_{oc} : Gas oil cracking rate	R_{if} : Rate of total feed
D_{tf} : Density of total feed	C_{tf} : Conversion on total feed
T_{ra} : Reactor temperature	C_{cat} : Catalytic reaction carbon
R_{cf} : Total carbon forming rate	R : Gas law constant
P_{ra} : Reactor pressure	C_{rc} : Carbon on regenerated catalyst
H_{ra} : Reactor Catalyst Holdup	C_1, C_2, C_3 : Fitting constants
k_{cr}, k_{cc} : Spesific unit	T_{rg} : Regenerator dense phase temperature
K_{or} : Oxygen reaction coefficient	Y_{gl} : Gasoline yield
E_{or} : Activation energy of oxygen reaction	R : Gas law constant
R_{cb} : Coke burning rate	H_{rg} : Heat of coke burning regeneration
R_{ai} : Rate of regenerator air	K_{od} : Oxygen diffusion coefficient
O_{fg} : Flue gas oxygen	F_{gl} : Gasoline yield factor
P_{rg} : Regenerator pressure	I_{gl} : Gasoline re cracking intensity
Y_{gs} : Gas yield	Y_{co} : Cycle oil yield
Y_{ck} : Coke yield	
D_{gl} : Density of gasoline	

APPENDIX B - ARTIFICIAL NEURAL NETWORK MODELING

Artificial neural networks (ANNs) are computational tools that have the structure of the neurons in the brain. In an ANN, each neuron has multiple inputs and a single output. The output of the neuron is given as

$$y_i = f\left(\sum_{i=1}^n w_i x_{it} - \theta\right) \quad \dots(4)$$

where t is the time, n is the number of inputs, y_i is the output, x_{it} is the i th input, w_i is a weight, θ is the bias of the neuron and $f(\bullet)$ is the activation function. The activation function can be linear or nonlinear. Weight w_i takes the positive value in the case of excitation and takes the negative value in the case of inhibition. In an ANN, neurons can be organized in two forms: recurrent net and a feed-forward net. In a recurrent net all the neurons are interconnected to each other. In a feed-forward net neurons are organized in layers: one input layer, hidden layers and one output layer. Data flows through input layer to output layer. The structure of ANNs enables them to learn, approximate functions, and classify patterns. These abilities of ANNs make them powerful tools for modeling control systems. To model control systems mostly feed-forward nets with sigmoidal, signum or Gaussian activation function and so on are used. The weights in these nets are commonly updated using back-propagation learning algorithm. Defining an error as the difference between the desired output of the network and the actual output of the network, back-propagation learning algorithm minimizes the sum of the mean square error using a gradient search technique. Back-propagation is the most commonly used training algorithm for neural networks. In a back-propagation algorithm the weights are updated as follows:

$$\Delta w_i(t) = -\eta \frac{\partial E(t)}{\partial w_i(t)} + \alpha \Delta w_i(t-1), \quad \dots(5)$$

where η is the learning rate, α is the momentum, and $E(t)$ is the error. Figure 12 illustrates the topology of the back-propagation neural network.

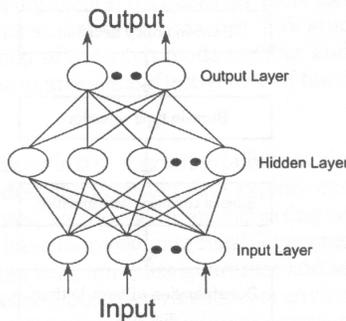


Figure 10. Topology of the back-propagation neural network

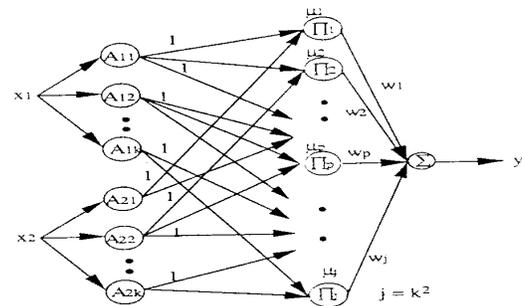


Figure 11. A Structure of a FNN

APPENDIX C – FUZZY NEURAL NETWORK

The utility of fuzzy sets lies in their capability in modeling uncertain or ambiguous data so often encountered in real life. There have been several attempts recently in making a fusion of fuzzy logic and neural networks for better performance in decision making systems. The uncertainties involved in the input description and output decision are taken care of by the concept of fuzzy sets while the neural net theory helps in generating the required decision regions. Fuzzy sets are powerful tools to model uncertainty. A fuzzy set is a function from a set of objects to $[0, 1]$. Since control systems have to deal with a highly uncertain environment, fuzzy sets are very good tools to model control systems. But fuzzy sets do not have learning capabilities to adjust themselves according to the dynamic nature of a control system. This limitation of fuzzy sets inspired researchers to combine the learning ability of ANNs and the quantification of uncertainty ability of fuzzy sets in fuzzy neural network models (FNN). In a FNN structure as seen in figure 13, fuzzy neurons are used. Fukuda and Shibata (1992) gives as an example Ichihashi's (1991) model where A_{ip} and w_p represent the membership function of the i th input in the p th rule and consequence of the p th rule respectively. The result of the p th rule, μ_p , and the output, y , are given as

$$\mu_p = \prod_{i=1}^n A_{ip}(x_i), \quad \dots(6)$$

$$y = \sum \mu_p w_p.$$

APPENDIX D: A SAMPLE FLUID CATALYTIC CRACKING UNIT SUMMARY REPORT OF TUPRAS REFINERY (5-February-1997)

Fresh feed rate	m3/d	2218	t/d	2017
Recycle feed rate	m3/d	103	t/d	111
Total feed rate	m3/d	2319	t/d	2128
Combined feed rate	m3/m3	1.05		
Gas oil conversion	vol %	84.30	wt %	82.41
380 conversion	vol %	87.12	wt %	85.36

<u>YIELDS</u>	<u>m3/d</u>	<u>t/d</u>	<u>vol%</u>	<u>wt%</u>
Secondary absorber off gas	5381/hr	124	-	6.14
Liquefied petroleum gas	634	358	28.61	17.77
Gasoline	1418	1053	63.98	52.20
Corrected gasoline	1481	1112	66.80	55.15
Light cycle gasoil	191	185	8.62	9.19
Heavy cycle gasoil	0	0	0	0
Clarified oil	157	169	7.08	8.39
Coke	-	111	-	5.52

Liquid recovery	2400	-	108.30	-
Liq. recovery (gas included)	-	-	126.91	-
Weight recovery	-	2001	-	99.21

PROCESS OPERATING VARIABLES

Blower outlet press.	Kg/cm2		3.11	
Blower outlet temp.	C		212	
Hydrogen on coke	wt%		14.71	
Air to coke ratio	t/t			
Air to regenerator	m3/hr	51905		
Air to atmosphere	m3/hr	0		
Torch oil	m3/d	0		
Cat. stripping steam	kg/hr	1800		
		Lb/mlb cat.	1.75	
Cat. Circulation rate	t/min	17.18		
Cat. To oil ratio	t/t	11.63		
Compressor	rpm	9800		
Blower	rpm	4390		
Valve open. Of LRC-1	%	46		
	TRC-1		%	58
Pressue drop LRC-1	kg/cm2	0.37		
	TRC-1	kg/cm2	0.17	

REACTOR OPERATING VARIABLES

Raw oil preheat out temp.	C	227
Raw oil furnace out	C	254
Combined feed	C	251
Riser outlet	C	533
Vapor outlet	C	528
Cat.bed dense phase	C	538
Cat. bed dilute phase	C	533
Cat.bed dense phase Temp	C	667
Catalyst bed level	meters	2.06
Catalyst bed density	t/m3	0.28
Pressure	kg/cm2	2.27
Preheat furnace fuel	m3/hr	*
Fuel oil equivalent	m3/d	*

FRACTIONATOR OPERATING VARIABLES

Temperatures&Pressures	C	kg/cm2
Top		141
LCGO Draw off	240	

LABORATORY TEST RESULTS

<u>Raw Oil</u>		
Gravity	API	24
Viscosity	ssu at 122 F	139.8
Conradson Carbon	wt %	0.11
Pour point	deg F	+95
UOP K factor		11.80
Sulphur	wt%	-

<u>Secondary Absorber Off Gas</u>		
Spesific Gravity		0.781
Hydrogen	vol %	11.41
Inerts	vol%	14.85
C3+Heavier	vol%	4.09
Nitrogen	vol%	13.99
H2 to C1 Ratio		0.51

Whole Crack Naphta

Gravity	API	59.10
Astm Dist. 10%	deg. C	48
Astm Dist. 50%	deg. C	95
Astm Dist. 90%	deg. C	178
Astm Dist. E.point	deg. C	228
RVP	PSI	9.8
Octane F-1	clear	94.6

Light Cycle Gasoil

Gravity	API	14.4
Astm Dist 10%	deg. C	242
Astm Dist 50 %	deg C	260
Viscosity	ssu at 122F	32.1
Pour point	deg. F	<-5

Clarified Oil

Gravity	API	-0.4
Viscosity	ssu at 122	236
FB* Catalyst content	lb./usg	0.014

Liquified Petroleum Gas

Density	at 15 deg. C	0.565
C3	vol %	37.84
C4	vol %	59.84

Equilibrium Catalyst

LECO Carbon	wt%	-
Bulk density	t/m3	0.9032

Flue Gas Analysis

CO2/CO in Flue Gas	mol/mol	1.76
CO in Fue Gas	vol %	5.8
O2 in Flue Gas	vol %	0.8

REGENERATOR OPERATING VARIABLES

cat. Bed dilute phase	C	690
flue gas east stack	C	690
flue gas west stack	C	
cat. Bed. Level	meters	2.91
cat. Bed density	t/m3	0.45
Pressures	kg/cm2	2.85

CATALYST TYPE&INVENTORY

Reduxion T	wt%	39.56
Advance 88 TI	wt%	59.44
Octidyne Extra	wt%	1
Reactor	t	13.52

HCGO draw off	319		Regenerator	t	33.96
Bottom	368	2.14	Stripper	t	22.62
Reflux drum	36	1.27	Total	t	70.1
7G-4 outlet		8.30	Loaded	kg/d avg.	1467
			withdrawn	kg/d avg.	952
			Losses	kg/d avg.	645
			Usage rate	lb/bbl ff	0.253

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