IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received October 29, 2021, accepted November 16, 2021, date of publication December 10, 2021, date of current version January 12, 2022.

Digital Object Identifier 10.1109/ACCESS.2021.3134931

Optimization of Distribution Control System in Oil Refinery by Applying Hybrid Machine Learning Techniques

ALI HUSSEIN HUMOD AL JLIBAWI[1], (Member, IEEE), MOHAMMAD LUTFI OTHMAN[1], (Senior Member, IEEE), ARIS ISHAK[1], BAHARI S. MOH NOOR[2], AND AL HUSEINY M. SATTAR SAJITT[3]

[1]Advanced Lightning, Power and Energy Research (ALPER), Department of Electrical and Electronic Engineering, Faculty of Engineering, Universiti Putra Malaysia (UPM), Serdang 43400, Malaysia
[2]Department of Electrical and Electronic Engineering, Faculty of Engineering, Universiti Putra Malaysia, Selangor 43400, Malaysia
[3]Faculty of Engineering, University of Wassit, Kut 52001, Iraq

Corresponding authors: Ali Hussein Humod Al Jlibawi (alihhumod@gmail.com) and Mohammad Lutfi Othman (lutfi@upm.edu.my)

This work was supported by the Geran Putra Berimpak—Universiti Putra Malaysia (GPB—UPM) under Grant UPM/800-3/3/1/GPB/2019/9671700.

ABSTRACT In this research, prediction of crude oil cuts from the first stage of refining process field is laid out using rough set theory (RST) based adaptive neuro-fuzzy inference system (ANFIS) soft sensor model to enhance the performance of oil refinery process. The RST was used to reduce the fuzzy rule sets of ANFIS model, and its features in the decision table. Also, discretisation methods were used to optimise the continuous data's discretisation. This helps to predict the two critical variables of light naphtha product: Reid Vapor Pressure (RVP) and American Petroleum Institute gravity (API gravity), which detect the cut's quality. Hence, a real-time process of Al Doura oil refinery is examined and the process data of refining crude oil from these two sources improve the knowledge provided by the data. The response variables represent the feedback measured value of cascade controller in the top of the splitter in crude distillation unit (CDU) in the rectifying section, which controls the reflux liquid's flow towards the splitter's head. The proposed adaptive soft sensor model succeeded to fit the results from laboratory tests, and a steady-state control system was achieved through an embedded virtual sensor. The predictive control system has been employed using cascade ANFIS controller in parallel with the soft sensor model to keep the purity of the distillate product in the stated range of the quality control of oil refinery. The results obtained from the proposed ANFIS based cascade control have no over/undershoots, and the rise time and settling time are improved by 26.65% and 84.63%, respectively than the conventional proportional-integral-derivative (PID) based cascade control. Furthermore, the results of prediction and control model are compared with those of other machine learning techniques.

INDEX TERMS Predictive control system, crude distillation unit (CDU), embedded soft sensor, machine learning techniques, cascade controllers, reid vapor pressure, API, reflux ratio, fuzzy inference system (FIS), decentralized control system (DCS).

I. INTRODUCTION

Generally, the petrochemical and oil refinery industries employ advanced control systems in order to improve the product quality and yield, thereby maximising the operation of the process by reducing the unnecessary expenses. The crude distillation unit (CDU) is one of the most significant process in chemical process industries. As, all the crude oil initially must pass through a CDU before loading into the subsequent loading units [1]. Therefore, effective design of controller or sensor to maintain the device operation within the control zones is a major challenge. The CDUs in oil refineries are the most important, dynamic and energy-intensive processes. Although there are no chemical reactions during the

The associate editor coordinating the review of this manuscript and approving it for publication was Wenbing Zhao.

dismantling phase, the volume of mass and energy consumed, the types of machinery, the operational and environmental pressure, and competing financial objectives make the CDU system a challenging control problem. This study examines a process system at Al Doura oil refinery in Baghdad, Iraq, which processes around 70000 bbl./day of light and heavy crude oil [2]. To control the process, the advanced control techniques of predictive control or model predictive control was widely used in the industrial process control. Typically, the predictive model forecast the future performance of the process based on historical process knowledge and forward-looking inputs. Further, the model displays the potential behaviour of the system. However, their design requires a computer program to play with various control laws and to see the resulting performance [3].

On the other hand, distillation is the common method for separation of final products in petroleum industries. It consists of different elements which is either used to transfer the heat or to improve the mass transmission. A typical distillation column includes vertical columns where trays or plates separate the components, a boiler to provide heat for the required vaporization from the bottom of the column, a cooling condenser for condensing the vapour from the top of the splitter column. The calculation of distillation splitter column in this paper is based on a real-time oil project to create a light naphtha processing plant for increasing the control systems' utility value. The plant has a nominal capacity of 24000 kg/hr of light naphtha, which run for 24 hours a day and approximately 350 working days a year which is considered to be seven percent of the total crude oil products. The performance of the processing products is the purity of the distillate products, X_D in the range equal of 96 to 98% and the surfaces' impurity, X_B equal to or less than 2%. Further, many traditional or advanced distillation control systems assume that the column is working at constant pressure. However, the variation in the pressure makes the control design complex and reduces the efficiency. The column has 20 trays and is simplified by grouping several components to model the column dynamics. The splitter column comprises of three sections namely, feed section, rectifying section, and stripping or re-boiling section. A mathematical model was introduced for simulation analysis of splitter distillation column with energy equilibrium (L-V) structure control system for feasibility study and design of petroleum project [4]. To achieve the required production rates with product quality, each distillation column control should meet the set stable conditions for column operations, regulate the column operation to attain the required specification of products with minimum energy consumption and maximizing the product yield.

Moreover, the process variables like temperature, pressure, flow rate, level and composition must be monitored and controlled in all the distillation processes. These process variables within a distillation system are interlinked with one another, whereby a change in one process variable will result in change in other process variable. Thus, in column control, one should be looking at the whole column rather than focusing on any particular sections. However, each process variable has its own control loop that consists of a sensor, transmitter, and control valve. The control loop keeps track of the associated process variable using a sensor measurement and send the information to decentralized control system (DCS) by transmitter. Then, the corrective action is made through adjustment of process variable by varying the control valve. Subsequently, the streamflow rate is adjusted, and a desirable variable is being controlled. The above step is repeated continuously virtually in the loop, hence called 'control loop'. In [5], a predictive control concept was used in online with success method to determine the global optimization. This method operates effectively for complex systems with unpredictable changes and uncertainties. The predictive controller often estimates the variation in the dependent variable that caused by the independent variables. In [6], a conventional proportional-integral-derivative (PID) controller is employed for regulating the independent variable of the process. However, the uncontrolled independent variables are considered as interruptions and depend variable as other control objectives or process limitations. These studies consider a linear model which fails to describe the real-time process nonlinearities. However, the design of controller for the non-linear process using the conventional method control schemes is a cumbersome process. Hence, artificial intelligence-based control technique is proposed in this research work for providing adaptive solution of dynamic process. The main contributions of the proposed research work are as follows:

- Propose and design an RST based ANFIS model for prediction and control of Al Doura oil refinery process to predict the RVP and API of light naphtha product and also control the process for reaching the steady state with minimum settling time for change in input of the process.
- Develop an Al Doura oil refinery real-time process model in MATLAB/Simulink and implement the proposed intelligence-based prediction and control model for the process.
- Compare the performance of RST-ANFIS based prediction of light naphtha quality with other intelligence techniques of linear regression, linear support vector machine and feed-forward neural network in terms of root mean square error, determination of correlation and training time.
- The performance of ANFIS based cascade control scheme is compared with other forms of control such as conventional PID, fuzzy logic control, fuzzy tuned PID control, a hybrid genetic algorithm and fuzzy logic control approach in terms of over/undershoots, rise time and settling time.

II. LITERATURE REVIEW

One of the most critical processes at any refinery is the CDU, where the atmospheric distillation takes place. In this process, the first stage of crude oil break-down occurs and then the final products are refined by various techniques. The distillation curves and boiling ranges are the typical distilled products obtained from CDU which helps to determine the efficiency along with the grade of gap or overlap between the cut points of two identical crude oil fractions. The gap/overlap cannot be precisely measured but determined by laboratory experiments or tests in factories. Therefore, an index that closely related to the product extraction temperature provides accurate measures of the plant's efficiency and control. The non-linear and time-variable existence of industrial processes motivates the development of advanced control techniques. The relative gain array (RGP) method was used to find the highest magnitude relation between the adaptive predictive (AP) control model's input and output. Based on this analysis, each pair of input-output variables, and the AP controller are set. The simulation was performed using a strategy of AP regulation and simulated the same series using a decentralised PID control (10 PID controllers), optimised by Luyben techniques. In this study, the results of proposed control scheme were in contrast with classic decentralised scheme [3]. The combination of wavelet neural network (WNN) with line-up competition algorithm (LCA) were employed for optimisation of CDU operation in [7]. This study aimed to enhance the profitability of the CDU process by optimising its operation of process control. The performance of suggested method is validated with back propagation neural network (BPNN) and radial basis function neural network (RBFNN) based process control. The results reveal that the proposed WNN model can accurately predict the CDU operation with other techniques presented [7]. The data-driven soft sensor is another major concern of many researchers as it helps in monitoring the production lines quality, predictions of the hard measure parameters, replacement and support of physical sensors in case of deterioration and supporting control systems in manufacturing systems. A wide range of statistical inference and machine learning techniques have been used in data-driven soft sensors, which includes the principal components regression (PCR), partial least square regression (PLSR), support vector machine (SVM) and artificial neural network (ANN) [8]. The machine learning techniques are widely applied in different industrial fields for forecasting, predicting or classifying the product quality during batching and continues production lines. In case of food processing industries, these techniques are used to forecast the kinetics of food drying for different types of dryers. A Mamdani based fuzzy logic system was used to predict the moisture ratio and determine the drying kinetics of onions and similar analysis was made using ANN. The ANN shows superior performance to forecast the drying kinetics of onion [9]. Further, various data-driven approaches have been proposed for online prediction and process tracking in recent years. The principal component analysis (PCA) which includes auto-regression with exogenous variables (DARX) model, also known as state parameters ARX (SDARX). The SDARX model is trained with different set of input variables and gives superior performance in terms of correlation coefficient, root mean square error (RMSE) and mean absolute error compared to other data-driven soft sensor models [10]. In real-time, the inferred qualities' equations' biases are modified with standard laboratory results. Until identifying these attributes as a control variable for the controller, multiple laboratory findings were added in order to obtain a healthy estimate. The inferred qualities are the four primary commodity qualities, heavy naphtha, light diesel and heavy diesel, 95 per cent distillation points and kerosene flash points. Inferential measurements have been developed to monitor these qualities. All qualities have been inferred on the basis of statistical regression of empiric results. The statistical regression improved the yield of naphtha, straight run naphtha and kerosene [11].

A recurrent neural network (RNN) based non-linear autoregressive model with exogenous input (NARX) model was used in automotive industry to predict the area of contact of vehicle tire with ground surface. In this study, the differential evolution-based optimization technique was employed to train the network by changing network weights and bias values [12]. On the other hand, deep learning technique was used as soft sensor in petroleum refinery process/CDU to estimate and predict the online quality of American Society for Testing Materials (ASTM), 95% cut point temperature of heavy diesel. The results obtained was compared with other intelligence techniques of single hidden layer neural network, SVM, partial least square (PLS) and neural network partial least square (NNPLS). The study reveal that the deep learning based deep network outperforms in terms of RMSE [13].

The authors in [14] estimate the distillation end point (D95) based on data-driven soft sensor by applying different linear and nonlinear identification methods like Box Jenkins (BJ), Output Error (OE), and Hammerstein-Wiener (HW) model. The results obtained from BJ model was significantly predominant in terms of Final Prediction Error (FBE), RMSE, and absolute error than other linear and non-linear models presented. A wavelet transform based neural network method was applied to model the soft sensor in the petrochemical production process industries like Fluid catalytic cracking unit (FCCU). The model was used to estimate the dry point of the cruse gasoline of FCCU fractionator. The method of fusion was approved to be efficient to improve the performance of soft sensor of dry point prediction of crude [15]. A PLSR in combination with distillation curves (ASTM D86) from regular test were used to predict the vapor pressure of gasoline [16].

Further, an adaptive neuro-fuzzy inference system (ANFIS) modelling based soft sensor was used in the prediction of steel machine responses (metal removal rate and tool wear) and the performance was compared with ANN. The result shows that the prediction accuracy is higher for ANFIS compared to ANN technique [17]. In food drying processes industry, the ANN and ANFIS model were used to predict the moisture ratio (MR), energy utilization (EU), energy utilization ratio (EUR), exergy loss and exergy efficiency of onion slices drying process by Multi-Stage Semi- Industrial

Continuous Belt. In this case, both the ANN and ANFIS model are trained based on trial-and-error approach [18]. The ANFIS model was also used to predict the wear coefficient based on the condition monitoring in Archard's wear model. The proposed method shows better performance in terms of normalization RMSE for accurate wear prediction [19]. Thus, the effectiveness of ANFIS has been proven in various literature works for controlling the different processes. Hence, in this research an attempt has been made to design the soft sensor for CDU and the performance is measured in terms of RMSE and coefficient of determination.

A. PREDICTIVE CONTROL

Most manufacturing processes widely uses the PID controller compared to other advanced control techniques due to its simplicity of implementation in real-time. However, strategies in tuning the gain parameters of the PID controller is a major challenge. Conventionally, the Zeigler-Nicholas method was widely used for tuning the controller parameters. However, this method of tuning is ineffective for wide range process operating conditions. Hence, numerous advanced techniques were developed to tune the gain parameter of the PID controller namely Genetic Algorithm (GA), ANN, Practical Swarm optimization (PSO), Fuzzy logic controller (FLC) and so on [20].

In this research, an advanced predictive control system is employed in oil refinery process. Initially, the modelling of soft sensor to predict the target output of light naphtha Reid Vapor Pressure (RVP) and American Petroleum Institute gravity (API) is carried out. Then, the predictive control system which is an adaptive virtual control that produces feedback for the entire system. In this study, an ANFIS based PID controller was used in distributed control system of CDU.

B. INFERENTIAL MEASUREMENT

The principle behind the inferential is quantifying a stream property from readily available process measurement, such as temperature and pressure, which would be otherwise too expensive or time-consuming to measure directly in real-time. With laboratory analysis, the accuracy of inference was tested periodically. Inferential was used instead of real analysers in online, both for operator information cascaded to the process controller base layer or multivariable controller. By designing and implementing soft sensors, the product quality can be continuously measured, and inferential control methods were used. Al Doura oil refinery/ second atmospheric unit (CDU) was designed and built by PROKOP ENGINEERING BRNO/ Czechia. The control system in Al Doura oil refinery was microprocessor-based, distributed, modular instrumentation system, and factory tested. The physical sensors were distributed in all the plants [2].

Over the last few decades, vast interest in development of inferential model also called inferential sensor. This sensor helps to predict the real-time estimate of the desired process variable that reduces the measurement devices and improves the system quality through tight control of the process. In this research, an ANFIS model of soft sensor was used to predict the RVP and API of light naphtha product. The proposed ANFIS controller possesses the advantages of smoothness from fuzzy inference system (FIS) and adaptability from NN. As the FIS is unable to handle the complex process with incomplete data which can be resolved through self-adaptive property of ANFIS [23]–[25].

C. DISTRIBUTED CONTROL SYSTEM IN OIL REFINERY

The decentralised control system (DCS) is a computer based supervisory control system provided for controlling the process units and CDU utilities. Advanced process controls implemented in DCS includes crude heater passes for temperature balancing control, crude heater control for control heater duty and outlet temperature, crude tower multivariable control, stripping steam/products ratio control, crude tower overhead receiver non-linear level control, over flash control, light naphtha stabiliser liquefied petroleum gas (LPG) control, light naphtha RVP, and API control. The DCS and transmitters used in Al Doura oil refinery are from Japan/YOKOGAWA technologies.

D. SYSTEM STABILITY AND PROCESS VARIABLES BALANCE

The plant's performance and preservation of the machinery's full efficiency depends entirely on the operators' care to demonstrate the whole system. Certain laws must be followed with a specific frequency and care to ensure smooth running, and the output in compliance with the quantities and characteristics envisaged. The following are essential process variables for distillation unit: column pressure, column feed temperature, column reflux and pump rounds, column stripping steam, and column product withdrawal. When evaluating the effects of a measured process adjustment, it should be considered that each factor exerts some impact on the others and is influenced by them. Needless claims, after appreciating its potential effect on the system's overall balance, any single step must be carefully prepared [2].

E. SPLITTING SECTION OF CDU START-UP

The operation of processes and its condition need to be understood for designing the control system of any industrial process. The splitter column or C04 in Al Doura oil refinery is the last column and final stage of CDU. Light naphtha was produced after distillate heavy naphtha comes from the stabiliser column. Strat-up of the splitter section called distillation phase (column C04, reflux drum D03, reboiler E14, cooling coil A03 and the corresponding pipeline) is in progress after the heating-up of column C03 by side pump around (PA).

The process variables of the stabilizer (CO3) and splitter (CO4) are presented in Table 1. If the section is stabilised, it is possible to make minor changes to the respective parameters to achieve the necessary product quality. For the sampling

TABLE 1. Process variables of stabilizer CO3 and splitter CO4.

Symbols	Variable	Column Number
TI033	Temperature of the feed of heavy naphtha.	Stabilizer CO3
TI031	Temperature at the top of stabilizer.	Stabilizer CO3
PI028	Pressure at the top of stabilizer.	Stabilizer CO3
TI032	Temperature of the under reflux of stabilizer.	Stabilizer CO3
TI034 (A, B)	Temperature of the above reboiler of stabilizer.	Stabilizer CO3
TI037	Temperature at the bottom of stabilizer.	Stabilizer CO3
PI027	Pressure at the bottom of stabilizer.	Stabilizer CO3
TI036	Temperature of the feed of stabilized naphtha.	Splitter CO4
TI035	Temperature at the top of splitter.	Splitter CO4
PI030	Pressure at the top of splitter.	Splitter CO4
TI038 (A, B)	Temperature of the above reboiler of splitter.	Splitter CO4
TI039	Temperature at the bottom of splitter.	Splitter CO4
PI029	Pressure at the bottom of splitter.	Splitter CO4

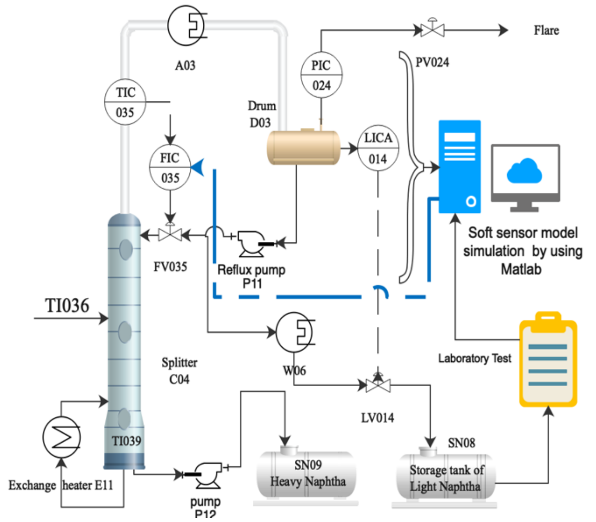

FIGURE 1. Splitter column PI&D diagram of CO4 in CDU in Al Doura oil refinery.

of light naphtha, individual heavy naphtha items, the sump number SN08, and respective SN09 are exploited [2].

The functional condition is modified based on the product flow rates after start-up, and laboratory tests deliver the quantities and qualities of the desired goods. The flow rates, temperature and pressures defined in the process variables standard are estimated values in the standard refinery diagram. Laboratory test of the vapour is the sequence analysis for normal operating conditions.

In this research, a real-time process of Al Doura oil refinery PI&D was studied and the PID controller of the real-time process is tuned using the intelligence based ANFIS technique. The detailed modelling of the splitter column C04 in Al Doura oil refinery PI&D is shown in Figure 1. The data for simulation of the Al Doura oil refinery process model is given in [2].

III. METHODOLOGY OF PREDICTION MODELS EMBEDDED INTO THE PROCESS

There must be a pressure delta between the stabiliser and the splitter column to ensure the flow of stabiliser bottom product to the splitter. The process variables that have been collected from the oil refinery process for the specific product of light naphtha are fifteen independent variables as given in Table 1 and two output (dependent variables) which are API and RVP.

The correlation relationship between process variables with both API and RVP are obtained using Pearson correlation coefficient analysis to find the strength of the relations between them. The final process variables have been deducted into eight process variables. Then, the final results of correlation coefficient will be used in the proposed model. This deduction in process variables are obtained using rough set theory (RST) which is proposed by Pawlak (1981) as a new mathematical tool for handling unclear concepts. While machine learning and data mining may be utilized alongside rough set methods or can also be incorporated into rough set systems. This concept has been proven to be more effective for inducing rules and finding features (semantics-preserving dimensionality reduction) [34]. The research method proposes in this study, uses two platforms Rstudio and MATLAB, first platform has huge number of tools to perform RST and the result of Rstudio will be expended to MATLAB ANFIS Model. The Rstudio will give different sequences of the redact attributes that will be examined by using MATLAB to find the best performance of API and RVP Prediction.

A. CONFIGURATION OF ANFIS MODEL FOR API AND RVP

ANFIS is a technology for data learning using fuzzy logic to transform the input into the expected outcome through interconnected neural network (NN) processing elements and knowledge connections to trace the numerical inputs into an output. The structure of ANFIS model for both API and RVP in this research consist of five layers. ANFIS structure models has five inputs and one output. The inputs are extracted by using RST sequences. The ANFIS model consist of different layers: first layer (input layer) which include five variables for both API and RVP model product with two triangular membership function, second layer represent the FIS process (fuzzification) of the output of first layer, product is used as AND method and max is used as OR method. The sugeno type fuzzy inferential system has been used for both API and RVP models. The rule layer (third layer) where normalization

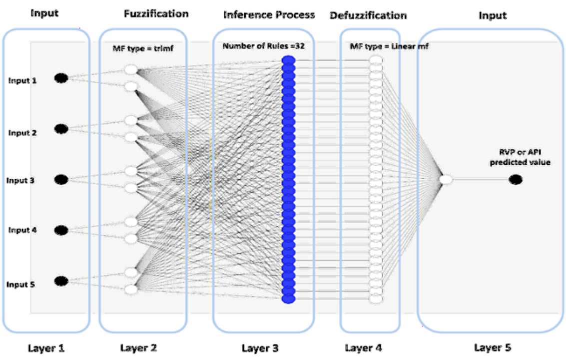

FIGURE 2. The general structure of ANFIS Model for both RVP and API.

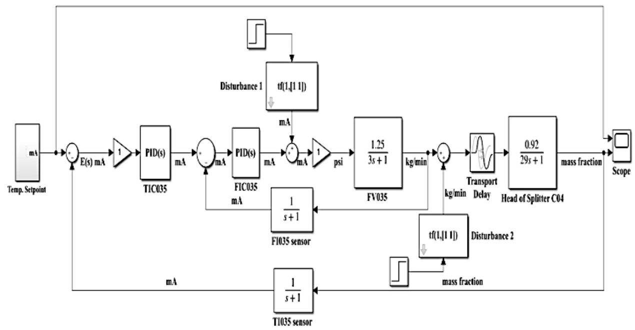

FIGURE 3. General block diagram of cascade PID controller in top of C04.

process occurs or what is called inference process. The fourth layer is the defuzzification layer. The method used in the two model of ANFIS are weighted average defuzzification (wtaver). The inference of normalization creates the output with a linear membership function in the output. The fifth layer or the summation layer for the output of defuzzification layer and the fuzzy combination outcomes are converted into crisp value [28]. Fig. 2 represents the structure of ANFIS model with different layers as detailed above with 5 inputs and one output model for prediction of RVP and API.

The prediction of RVP and API measure of light naphtha has been conducted for three types of crude oil from two different resources (Kirkuk, Basra and Basra Medium). The processing variables value were collected for two months. The collected data has been surveyed from the DCS of the control room. The laboratory testing data for light naphtha test were collected within the same sampling time of CDU's process variables. Different types of machine learning, and data mining techniques were applied after pre-processing the raw data. Neuro-Fuzzy based rough set theory and the quantile discretisation method model were chosen as the best fitting model to predict RVP and API as dependent or response variables from the independent variables of pressure and temperature variables of both stabiliser and splitter processes [29]. Rough set strategy has been used for redaction purpose of collected data and quantile discretization methods.

B. CASCADE CONTROLLER IN THE TOP OF CO4

The ANFIS based prediction model act as a soft sensor in order to predict the RVP and API of the product. Further, to enhance the performance an ANFIS based control strategy were used in rectifying section of the splitter in the place of conventional PID controller as shown in Fig. 3. This increases productivity and improves the quality. The detailed explanation on cascade controller in the top of splitter is discussed below:

- Setpoint: Temperature designed for the top of column TI035.
- Primary controller (master): TIC035 measures the top of CO4 temperature TI035 and probe the secondary controller FIC035 for more or less reflux flow rate.
- Secondary controller (slave): FIC035 measure and maintains flow rate directly.
- Actuator: Reflux flow rate valve FV035.
- Secondary process: Flow in the reflux supply line.
- Inner loop disturbances fluctuation in supply pressure from FV035.
- Primary process: Distillate (fractionation of light naphtha) in the top of the splitter.
- Outer loop disturbance fluctuation in the CO4 top of splitter temperature due to uncontrolled ambient conditions. Significant changes in the inflow TI036, and temperature of middle and bottom of splitter TI038 A, B and TI039.
- Secondary process variable reflux flow rate.
- Primary process variable CO4 top splitter temperature.

The cascade control is necessary if the process has more than one element which can affect a single process variable and treating each separately makes easier control of processes. One process variable that depends on more than one measure, might need more than one controller. Cascade controller and head of splitter designed by using FOPDT (First Order- Plus- Dead-Time), head of splitter temperature dynamic behaviours effect by the change of flow to the head of splitter. Changes of TI035 has its significant effects on both RVP and API of the light naphtha. The Reflux ratio which is by the way consequence on the distillate product purity (range of distillation should be 0.96-0.98). However, the extra sensor and controller tend to increase the overall equipment costs of the processes. Also, the tuning of cascade control systems is more cumbersome process as it requires tuning of two controllers. But the tuning procedure is quite straightforward which requires tuning of secondary controller manually and then the primary controller until the desired output is achieved.

IV. EMBEDDED SOFT SENSOR WITHIN DISTRIBUTED CONTROL SYSTEM

This research aims to analyse the soft sensor modelling in an oil refinery embedded into the control system at each refining process level. Data was acquired from physical sensors and instruments using MATLAB, data acquisition toolbox, instrument control toolbox, image acquisition toolbox. With MATLAB software, it is possible to acquire, analyse and visualise the data. Also, analysing data from the same environment saves time and enables live analysis, which is the objective of this research.

Philosophy of distillation control system has some of the general guidelines: column pressure generally controlled at a constant value, feed flow rate often set by the level controller on a preceding column, feed flow rate is independently controlled if fed from the storage tank or surge tanks, feed temperature controlled by a feed preheater. Before preheater, the feed may be heated by bottom product via feed/bottom exchanger, the top temperature usually controlled by varying the reflux, bottom temperature controlled by varying the steam to reboiler, differential pressure control used in packed columns to monitor placing condition, also used in tray columns to indicate foaming, and the compositions controlled by regulating the reflux flow and boiled-up (reboiler vapour).

The pressure is often considered as the prime distillation control variable, as it affects temperature, condensation, vaporization, compositions, volatilities and almost any process inside the column. Column pressure control is frequently integrated with the condenser control system. Reboilers and condensers are an integral part of a distillation system. They regulate the energy inflow and outflow in a distillation column. A column is controlled by regulating its material and energy balances.

A. CONTROL LOOPS DESCRIPTION

This section describes the control loop for the critical parameter of the CDU (flow, level, temperature, and pressure) as the target of the present research (Heavy and Light Naphtha). The control loop details were given in the user manual of the CDU of Al Doura oil refinery.

Reboiler control is required to provide an adequate response to column disturbances and protect the column from disturbances occurring in the heating medium. The reboiler boil-up is regulated either to achieve desired product purity or to maintain a constant boil-up rate.

Analyzer control such as gas chromatography usually measure the on-line composition. Other analysers include infrared and ultraviolet analyser mass spectrometers, refractive index analysers, etc. Analysers have the advantage of directly measuring the product quality and the drawbacks of high maintenance and slow dynamic response. They have a more significant downtime than other instruments and may be particularly troublesome when the stream analysed is fouling or contains impurities which interfere with the analyser internals. Analysers are prone to large measurement lags which translate into response delays in the control system. The primary sources of lags are process lags, sample transfer lags (the dead time in the line from the sampling point to the analyser) and analyser transfer lag (the time it takes to transfer the analyser sample components valves to the detector).

With analyser controllers, it is essential to minimize sample transfer lags. Vapour samples are preferred since they can travel faster. A liquid sample is often vapourised upon withdrawal if sampling lines are long. Heat tracing and insulation are usually required to keep the sample vapourised. The sample withdrawn is often much more extensive than what the analyser requires, with its unused portion returned to the process to maintain high velocities.

Column temperature control is possibly the most popular way of controlling product compositions. In this case, the control temperature is used as a substitute for product composition analysis. Ideally, both top and bottom compositions should be controlled to maintain each within its specifications.

By studying the above-mentioned controllers, we conclude that the effects by the top and bottom temperature controller of the splitter column. In practice, both products' simultaneous composition control suffers from severe ''coupling'' (interaction) between the two controllers, resulting in column instability. In the system shown, suppose that there are concentration changes in the feed conditions that result in lower column temperature. The top and bottom temperature controllers will respond by decreasing reflux and increasing boil-up, respectively.

If the two controllers' actions are perfectly matched, and the response is instantaneous, both control temperatures will return to their setpoints without interaction.

However, the two actions are rarely perfectly matched, and their dynamics are dissimilar - usually, the boil-up response is faster. The reflux and boil-up will ''cycle.'' The interaction can be avoided by controlling only one of the two product compositions. The on-line analyser can be used together with temperature control to control product composition. The central control action is rapidly performed by the temperature controller, while the analyser slowly adjusts the temperature set point to prevent off-specification product purity.

In the above set-up, delayed analyser response is acceptable, as its time lags become a secondary consideration. The fast temperature controller action renders this control method less sensitive to upsets and step changes in an analyser-only control system. Another advantage is that, should the analyser become inoperative, the temperature controller will maintain automatic control of the process.

Both controller FIC035 and TIC035 have a healthy relationship. Both are controlled by using ANFIS controller, the manipulated value of TIC035 which represent the master controller, and the setpoint for FIC035 represent the slave controller. The manipulated value of FIC035 is FV035 valve to control the flow of the product to the head of top splitter CO4. By using ANFIS soft sensor model as embedded sensor rule. The rule of the soft sensors ANFIS model of API prediction and ANFIS Model of RVP prediction predicts feedback to support and improve the feedback cascade controller of TIC035 and FIC035. Improvement of distillation quality of the final product of light naphtha controlled by the reflux ratio of the top of splitter CO4.

One new approach to soft sensing is to use high reliability online active simulation model connected to the plant information systems. In this research, the active simulator took a direct feed of information from the plant process instrumentation and control system, distribution control system, which could then predict process parameters not physically measured in the oil refinery plant. The model stored and archived the prediction values in the plant historian system. To clarify the thinking around soft sensors using dynamic simulation, proof of concepts was shaped. The first phase was to generate a high-reliability simulation model of the process plant on MATLAB simulator platform, which was validated against the actual process plant data.

Next, the model was tuned to match the existing plant operating conditions at a steady state. The model then links to the process instrumentation and distributed control system feed using the software interface. The interface is also coupled to an input data module for supplying offline inputs, such as ambient conditions and laboratory analysis of feed streams. The interface should be connected to the plant historian, so that the soft sensor and calculated parameters could be stored for future use. Linked simulation model should stabilise and settle in a steady state with predicted parameters computed by the simulation model. Virtual sensor could be employed instead of the actual online analyser for operator information, cascaded to base–layer process controller, or multivariable controllers.

MATLAB algorithms can be integrated with various DCS systems with open plate communication (OPC) toolbox. OPC toolbox provides access to live and historical OPC data directly from MATLAB and Simulink. As the OPC data can be read, write, and log from devices, such as DCS, supervisory control and data acquisition systems, and programmable logic controllers (PLCs). OPC toolbox works with data from live servers and data historians. Many techniques for acquiring data and exchanging information with the simulation platform such as Speedgoat technologies and others.

V. SOFT SENSOR SIMULATION MODEL

The simulation model shown in Fig.4 and Fig. 5 exhibits the five affected variables that redact from the decision table by using RST for each API and RVP soft sensor model which are represented by the independent or predictor variables that would be linked to RVP or API and symbolise the dependent or prediction parameters. As discussed earlier, the soft sensor models have four common variables between API and RVP which are feed temperature of stabiliser, the pressure at the head of splitter, the temperature at the bottom and head of splitter (TI033, PI028, TI039, TI035). In Simulink, the modelling optimisation of soft sensors are embedded and linked with the physical sensors through DCS by OPC virtually to collect the variables' value in real-time and predict the required parameters. The optimised model would improve the control system's ability to keep the process's safety human environment, and product quality. Also, to prove the effectiveness of the proposed method, a noise signals is embedded to get perfect results. In this research, the noise inside the industrial fields were left for mentioned. The present study creates soft sensor to mimic the analyser and obtains hard measure or time-consuming data.

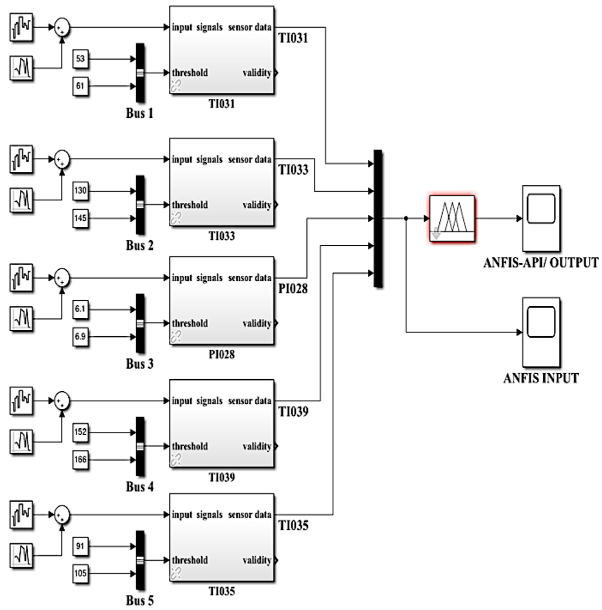

FIGURE 4. Soft sensor simulink model for API prediction.

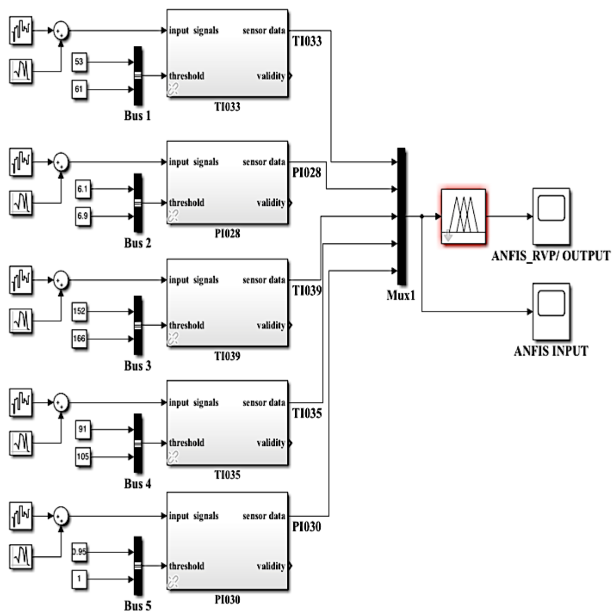

FIGURE 5. Soft sensor simulink model for RVP prediction.

VI. SOFT SENSOR IN THE REFINING CONTROL SYSTEM

Designing of two soft sensors that sense RVP and API of light naphtha could be embedded with cascade ANFIS based

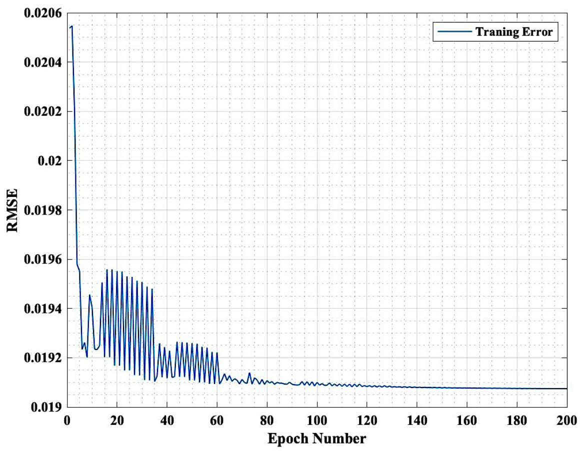

FIGURE 6. Training of ANFIS model for RVP prediction.

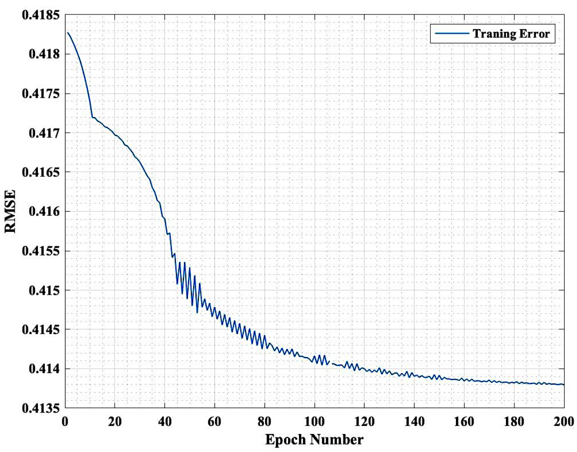

FIGURE 7. Training of ANFIS model for API prediction.

controller for the splitter's temperature and the flow rate controller for reflux flow rate to the top of the column. The reflux ratio affects the distillate products' purity (light naphtha), increasing reflux ratio between the return flow rate liquid to the head of the splitter with the rate of flow rate to outlet distillate product leads to increased distillation rate and improves the quality of light naphtha. Simultaneously, there are standards for designing the distillation columns that cannot be exceeded to keep the oil refinery production line's balance and stable [14], [31].

Evaporation losses are related to the true vapour pressure (TVP) of liquids at their storage temperature. The typical test for petroleum fractions is the RVP test defined by the American Society for Testing and Materials under the designation ASTM D323-56. The American Petroleum Institute describes the RVP test procedure more detail in [1], including the apparatus. Other API publications [2]–[4] show charts relating RVP and ASTM are boiling characteristics of gasoline and crude oils to TVP, a way to estimate RVP of blends, and the relation of RVP to evaporation losses.

TABLE 2. Comparison results of RVP prediction models.

No.	Method Name	Number of Attributes	R2	RMSE	Training Time (sec)
1	Linear regression by Microsoft Excel	8	0.77	0.292	3.7
2	Linear regression by MATLAB	8	0.73	0.0219	3.428
3	Regression tree	8	0.71	0.0227	2.96
4	Linear SVM	8	0.74	0.0217	2.023
5	Feed-forward Neural Network	8	0.85	0.021	5
6	ANFIS-based RST and quantile discretization method	5	0.90	0.0196	1.04

TABLE 3. Comparison results of API prediction models.

No.	Method Name	Number of Attributes	R2	RMSE	Prediction Speed obs/sec
1	Linear regression by Microsoft Excel	8	0.29	6.352	3
2	Linear regression by MATLAB	8	0.24	0.464	2.52
3	Regression tree	8	0.17	0.485	1.52
4	Linear SVM	8	0.23	0.464	1.18
5	Feed-forward Neural Network	8	0.446	0.682	2
6	ANFIS-based RST and quantile discretisation method	5	0.62	0.414	1.3

VII. RESULTS AND DISCUSSION

This section presents the results of proposed ANFIS based embedded soft sensor model for predictions of RVP and API of light naphtha from Al Doura oil refinery process. Also, discusses the ANFIS based controller for improving the overall performance of the process.

A. ANFIS BASED PREDICTIONS OF RVP AND API

The two soft sensors model developed using ANFIS for the prediction of RVP and API of Al Doura oil refinery process is presented in this section. The training of ANFIS model for prediction of RVP and API is shown in Figures 6 and 7, respectively. The results obtained from the recommended ANFIS based prediction model is compared with other regression and machine learning techniques. Tables 2 and 3 show that the predictions of RVP and API is predominantly significant by the proposed ANFIS model. The MATLAB platform was used for this purpose with its implementation is detailed as follows [27], [30]:

The final MATLAB code for prediction is listed below:

```
Load ('ANFIS_RVP_Model1.mat')
test_values= [ TI033 PI028 TI039 TI035 PI030]
rvp_result=evalfis(test_values,chk_out_fismat);
rvp_result
```

```
Load ('ANFIS_API_Model1.mat')
test_values= [ TI031 TI033 PI028 TI039 TI035]
api_result=evalfis(test_values,chk_out_fismat);
api_result
```

The MATLAB codes discussed were used for configuring system block in Simulink and embedded in control system of cascade controller and also consider soft sensors that support the physical sensors. The performance of the proposed method of predictions is assessed using wo important metrics such as determination of correlation (R^2) and root mean square error (RMSE). Also, the training time was compared in order to study the computational cost of the methods considered. From the results of Table 2 depicts the RVP prediction by regression and machine learning models, the correlation coefficient for ANFIS model is found to be 90% and is significantly higher than other model presented. On the other hand, the RMSE seen to be 0.0196 which is bit less than other models for prediction of RVP. However, the training time is comparatively very less of 1.04 s than other models considered. Also, the overfitting and underfitting problem in ANFIS-RST for RVP prediction model are avoided as the checking error is little higher than the training error which is equal to 0.0289 as inferred from training code of MATLAB and Figure 6 show the training plot. The ANFIS-RST model for API gravity prediction that work in parallel with RVP prediction model shows correlation coefficient higher than other models with value of 62%, also the RMSE is equal or close to other regression and machine learning models. Figure 7 shows the value of training plot that required more data to avoid under fitting of the model with new data and the checking error equal 0.486. Thus, it is seen that the RST-ANFIS based model outperforms overall in prediction of both RVP and API than other prediction techniques.

B. OPTIMIZED CONTROLLERS AT THE HEAD OF SPLITTER CO4

The dynamic behaviour and stability of the closed loop control system is studied with the following aspects: the dynamic performance of the top of splitter CO4 (rectifying section), the combination of the refluxing process, and the feedback from the cascade ANFIS based controller. The instrumentation is referred to as the feedback control loop or closed-loop system. Control system variables in the rectifying section of the splitter represents the flow rate or reflux rate to the head of splitter column FI035. The measured variable represents the reflux rate and reflux ratio (the rate between the flow rate of the head of the column and the flow rate of the final product). Finally, the manipulated variable signifies the pressure on valve FV035 to manipulate the flow rate. The disturbance variable denotes the inlet flow rate (feed rate of the splitter) in the middle and boiling rates in the bottom of the splitter. In this case, the inlet flow rate and the boiling rate are assumed to be integral by developing the derivative on rectifying processes' variables. Initially, the study was made with conventional PID controller with the respective transfer function for the system and considering the disturbances, the transmission behaviour and response plot of the current controller is presented in Figure 8. From the response it is seen that the quality of system parameters (Cascade PID controller for the rectifying section) of the top of the splitter with the simulation time of 1000s have overshoot with acceptable rising and settling time. The response of the system is further enhanced by the proposed ANFIS based controller and the results are compared with other intelligence techniques.

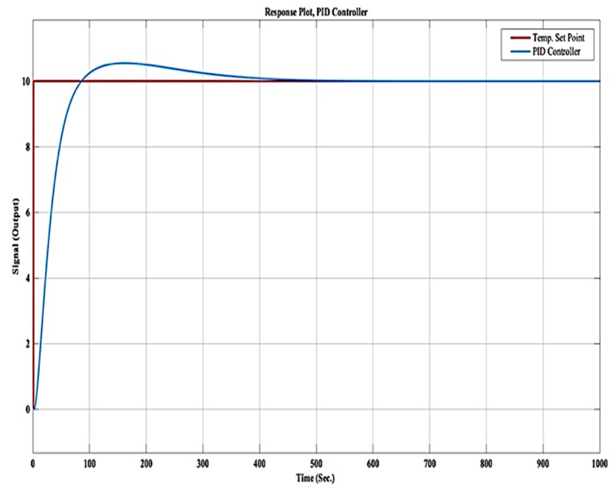

FIGURE 8. Response plot of cascade PID controller system in the top of splitter.

ANFIS is evaluate on a steady-state error response was developed to the controller system of CDU control system. In general, a network is a system that processes inputs and delivers outputs. A neural network is a system of computers that follows a pre-defined algorithm in order to do a certain task. Fuzzy logic inference systems (FISs) offer outputs that correspond to the result of numerous inputs. For non-linear applications, the use of ANFIS controller is implemented in CDU control system of Al Doura Oil Refinery process as it alters the membership functions to accomplish the performance targets by employing two cycles of pass learning: the forward pass and the backward pass. The ANFIS is a two-level approach which is used to create an initial fuzzy model using the rules obtained from the system's input output data. Then, the fuzzy rules are fine-tuned and refined using a neural network at the next level, leading to a more refined ANFIS model of the system. Using the ANFIS for the

TABLE 4. Comparison of the controllers for the head of splitter.

No.	Controller Type	Overshoot %	Undershoot %	Rise Time (sec)	Settling Time (sec)
1	PID	5.508	0	50.36	322
2	FLC	0	0	46.01	67.83
3	PID-FIS	0.0757	0	62.78	118.4
4	FLC_GA	0	0	41.44	59.49
5	**ANFIS**	**0**	**0**	**36.94**	**49.48**

head-splitter control system offers following advantages: It makes the process to respond quickly for various rectification requests. One of the keys to rapid liquid supply rectification is fast convergence. With ANFIS control the proposed control system of the head of splitter in CDU has improved control approaches. Thus, when the flow of liquid to the head of the splitter is halted, the reflux drum has refluxed the required amount of liquid. The flow rate of liquid, temperature, and pressure factors are examined while measuring the operation of the controllers. The results from Table 4 depicts the proposed ANFIS cascade controller gives excellent performance than other controllers of conventional PID, fuzzy logic controller (FLC), Fuzzy inference system (FIS) tuned PID, hybrid FLC with genetic algorithm (FLC_GA) in terms of Over/Undershoots, rise time and settling time. Also, the response shown in Figure 9 have no Over/undershoots for the case of ANFIS, FLC and FLC_GA controller and the overshoot is observed for the case of conventional and fuzzy tuned PID controller. Further, the rise and settling time were more significantly reduced for the proposed ANFIS based controller and the process settles faster to steady state. Essentially, the controller calculates P, I, and D, then multiplies each of these by the error, which is equivalent to SP-PV in direct acting.

The Control Variable is then calculated as the sum of all the parameter computations. It is tough to tune the most basic of PID loops, which is why these parameters have been included. The most frequently used tuning approach is known as trial and error. Although there are alternative ways that take a multi-step procedure to decide where the numbers should be, they may or may not work as wanted. After a disturbance has occurred, the aim of tuning is to minimize process oscillation around the setpoint.

C. OPTIMISATION OF CONTROL SYSTEM AT THE HEAD OF SPLITTER COLUMN TI035

The subsystem of RVP-ANFIS Model and API-ANFIS model embedded to the head of the rectifying section of the splitter column to study its effect on the system response. The Embedded soft sensors for API and RVP with the cascade ANFIS controller were replaced by switching with the head of splitter temperature (TI035) in case of the deterioration or drifting value of physical sensor. The head of the splitter's control system was supervised with the embedded soft sensors, which monitor their system by predicting light naphtha's

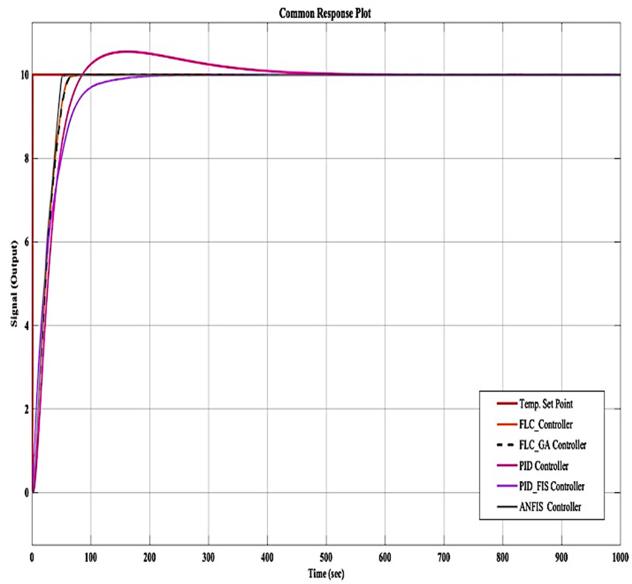

FIGURE 9. **Response plot of the improved control system.**

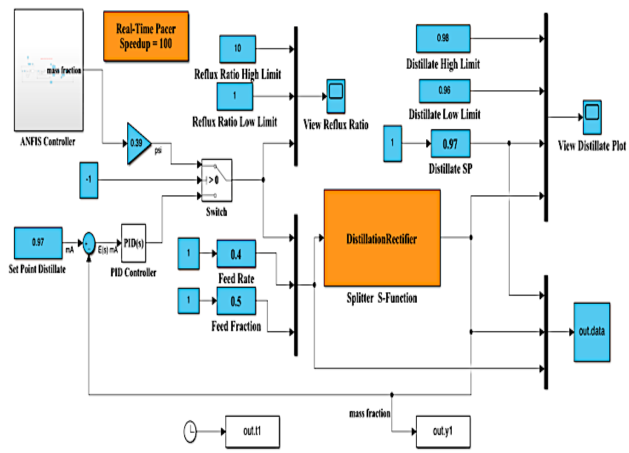

FIGURE 10. **Block diagram of the distillation simulation of the head of splitter controlled by the reflux rate of the optimised ANFIS controller.**

quality criteria. Rapidly switching soft sensor with the physical sensor improves the response of the controlled system.

The performance parameters (Peak overshoot, Rise time, settling time, and steady state error) are improved by using embedded soft sensor as a supported sensor in the control system and in parallel with ANFIS controller as a cascade controller for the head of splitter. By comparing both the control system simulations before embedding the soft sensors into the models and ANFIS controller, it is found that there is improvement in rising time and settling time. The improved system used to control the distillation ratio of the final product of the light naphtha. Figure 10 presents the optimised control system's block diagram to set the reflux ratio and the purity of the product in the distillation system of the splitter's rectifying section.

The reflux ratio is the boil-up rate to take-off rate ratio. In other words, the ratio between the amount of reflux that

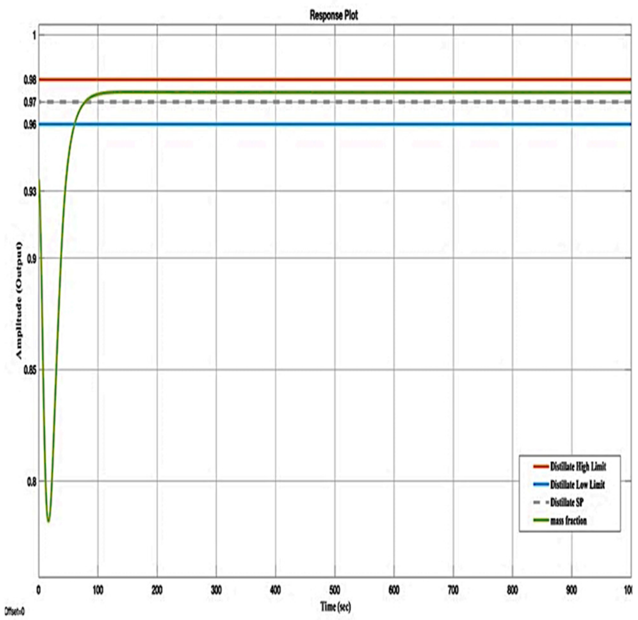

FIGURE 11. Response plot of the distillation section of the final product controlled by optimized cascade ANFIS controller.

goes back up to the column of distillation and the quantity of reflux the receiver collects (distillate) [32], [33]. Distillate rate of the light naphtha process limited between 0.96 to 0.98. This ratio is affected by the change of the reflux rate of the flow of light products to the head of the distillation column and how the head temperature of splitter TI035 masters the valve's reflux rate. The purity rates could be changed based on the conditions of the distillation columns and types of crude oil. The proposed system mimics the process of light naphtha product. The control system concludes that the optimised control system by adding RVP_ANFIS and API_ANFIS soft sensor model as a monitoring system and ANFIS Controller as cascade controller keeps the system in the range of distillate rate 0.96 to 0.98 and proves the visibility of the suggested model. Figure 11 shows the response plot of the distillation column controlled by the optimised cascade ANFIS controller. The higher the reflux ratio in the splitter column, the more vapour/liquid interaction will arise. So, higher reflux ratios typically indicate higher distillate purity. It also means that the distillate quantity would be lower. It is a compromise between purity and distillation speed to choose a heating temperature. Slow distillation rates provide higher purity but slower throughput. Lower purity but higher throughput is provided by quick distillation rates. The trick is to find the heating rate that gives the distillate's necessary purity while delivering an acceptable throughput.

VIII. DISCUSSION

Data mining and machine learning techniques could provide a better understanding of the prediction models in the oil refinery processes. The regression models in the advanced manufacturing systems, especially in the petroleum industries, are achieved by present neuro-fuzzy based on a RST with the quantile discretisation method. The suggested model provides good fitting and prediction of API and RVP of the light naphtha compared with other methods presented. Pre-processing the raw data collected from the oil refinery helped to improve the soft sensor modelling and provide good results. Applying raw data on the ANFIS model could reach the generalisation with few errors indicating the lack of data in the preliminary levels for training the model. Advanced process in information and computer technologies have lots of techniques that could link the process and predict the data through DCS. The simulation model presented improved the quality of monitoring through product quality prediction in real-time beside the prediction goal and achieved the advanced control system. The soft sensor signal was considered as feedback signal to the cascade control system for the affected variables. This also took into consideration of control system's stability and the steady-state errors for all the controllers. The optimisation of the control system in the head of the splitter supports the physical sensors by switching into ANFIS Controller. Thus, the proposed controller and soft sensor models work in parallel and achieved good monitoring and better results, and performance of the system stability.

IX. SUMMARY

Advanced control systems in manufacturing systems and complex industries like refining and petrochemical enhances the product quality and ensure good processing with less power consumption. Predicting the difficulty or cost of parameters is the major challenges for this type of industry since it affects the product quality for expensive materials. Therefore, the proposed research work suggests a ANFIS based soft sensor to replace the physical sensors in order to improve and support the control system, and to keep and monitor the quality of the final product like light naphtha. The RVP-ANFIS and API-ANFIS model-based RST and quintile discretization method as a predictive regression model is verified as a replacement for the temperature and pressure sensors in the head of the CDU's splitter to predict, monitor and control of Al Doura oil refinery process. Further, the ANFIS based cascade controller outperforms than other controllers of conventional PID, FLC, PID-FIS, FLC-GA in terms of over/undershoots, rise and settling time. Also, choosing a heating rate is a balance between the purity and distillation speed. The slow distillation rates give higher purity but slower throughput and vice versa. The key is to find the heating rate that offer the distillate's required purity while having an acceptable throughput. Generalization of the recommended models to employ as soft sensors approved to deal with new data. Thus, the suggested model can also work with the new processes and it's easy to maintain and upgrade.

REFERENCES

[1] A. S. Yamashita, A. C. Zanin, and D. Odloak, "Tuning the model predictive control of a crude distillation unit," *ISA Trans.*, vol. 60, pp. 178–190, Jan. 2016, doi: 10.1016/j.isatra.2015.10.017.

[2] P. E. Brno, "Operating manual of AL doura oil refinery," Middle Oil Company, Aldoura Oil Refinery, Manual Oper., Baghdad, Iraq, Tech. Rep., 2010, doi: 10.4324/9780203476154_chapter_9.

[3] A. Raimondi, A. Favela-Contreras, F. Beltrán-Carbajal, A. Piñón-Rubio, and J. L. de la Peña-Elizondo, "Design of an adaptive predictive control strategy for crude oil atmospheric distillation process," *Control Eng. Pract.*, vol. 34, pp. 39–48, Jan. 2015, doi: 10.1016/j.conengprac.2014.09.014.

[4] V. T. Minh and A. M. A. Rani, "Modeling and control of distillation column in a petroleum process," *Math. Problems Eng.*, vol. 2009, pp. 1–14, Jun. 2009, doi: 10.1155/2009/404702.

[5] T. Takahama and D. Akasaka, "Model predictive control approach to design practical adaptive cruise control for traffic jam," *Int. J. Automot. Eng.*, vol. 9, no. 3, pp. 99–104, 2018, doi: 10.20485/jsaeijae.9.3_99.

[6] T. Petroleum and R. Corporation, "Model predictive control of a crude distillation unit," *IFAC Proc. Volumes*, vol. 42, no. 11, pp. 1–6, 2005, doi: 10.3182/20090712-4-TR-2008.00144.

[7] B. Shi, X. Yang, and L. Yan, "Optimization of a crude distillation unit using a combination of wavelet neural network and line-up competition algorithm," *Chin. J. Chem. Eng.*, vol. 25, no. 8, pp. 1013–1021, Aug. 2017, doi: 10.1016/j.cjche.2017.03.035.

[8] L. Fortuna, S. Graziani, A. Rizzo, and M. G. Xibilia, "Soft sensors for monitoring and control of industrial processes," in *Advances in Industrial Control*. Springer, 2007, doi: 10.1007/978-1-84628-480-9.

[9] S. M. Jafari, M. Ganje, D. Dehnad, and V. Ghanbari, "Mathematical, fuzzy logic and artificial neural network modeling techniques to predict drying kinetics of onion," *J. Food Process. Preservation*, vol. 40, no. 2, pp. 329–339, Apr. 2016, doi: 10.1111/jfpp.12610.

[10] B. Bidar, J. Sadeghi, F. Shahraki, and M. M. Khalilipour, "Data-driven soft sensor approach for online quality prediction using state dependent parameter models," *Chemometric Intell. Lab. Syst.*, vol. 162, pp. 130–141, Mar. 2017, doi: 10.1016/j.chemolab.2017.01.004.

[11] S. Kemaloğlu, E. Ö. Kuzu, D. Gökçe, and Ö. Çetin, "Model predictive control of A crude distillation unit an industrial application," *IFAC Proc. Volumes*, vol. 42, no. 11, pp. 880–885, 2009, doi: 10.3182/20090712-4-tr-2008.00144.

[12] C. A. Duchanoy, M. A. Moreno-Armendáriz, L. Urbina, C. A. Cruz-Villar, H. Calvo, and J. de J. Rubio, "A novel recurrent neural network soft sensor via a differential evolution training algorithm for the tire contact patch," *Neurocomputing*, vol. 235, pp. 71–82, Apr. 2017, doi: 10.1016/j.neucom.2016.12.060.

[13] C. Shang, F. Yang, D. Huang, and W. Lyu, "Data-driven soft sensor development based on deep learning technique," *J. Process Control*, vol. 24, no. 3, pp. 223–233, Mar. 2014, doi: 10.1016/j.jprocont.2014.01.012.

[14] I. Mohler, Ž. U. Andrijić, and N. Bolf, "Development of soft sensors for crude distillation unit control," *IFAC Proc. Volumes*, vol. 44, no. 1, pp. 5407–5412, Jan. 2011, doi: 10.3182/20110828-6-IT-1002.01882.

[15] B. C. Xu, D. Y. Zhang, and X. L. Luo, "A new neural network soft sensing method based on the multi-resolution data fusion," in *Proc. World Congr. Intell. Control Automat.*, 2010, pp. 5915–5918, doi: 10.1109/WCICA.2010.5554503.

[16] G. Mendes, H. G. Aleme, and P. J. S. Barbeira, "Reid vapor pressure prediction of automotive gasoline using distillation curves and multivariate calibration," *Fuel*, vol. 187, pp. 167–172, Jan. 2017, doi: 10.1016/j.fuel.2016.09.046.

[17] S. O. Sada and S. C. Ikpeseni, "Evaluation of ANN and ANFIS modeling ability in the prediction of AISI 1050 steel machining performance," *Heliyon*, vol. 7, no. 2, Feb. 2021, Art. no. e06136, doi: 10.1016/j.heliyon.2021.e06136.

[18] M. Kaveh, R. A. Chayjan, I. Golpour, S. Poncet, F. Seirafi, and B. Khezri, "Evaluation of exergy performance and onion drying properties in a multi-stage semi-industrial continuous dryer: Artificial neural networks (ANNs) and ANFIS models," *Food Bioproducts Process.*, vol. 127, pp. 58–76, May 2021, doi: 10.1016/j.fbp.2021.02.010.

[19] X. Zhuang, T. Yu, Z. Sun, and K. Song, "Wear prediction of a mechanism with multiple joints based on ANFIS," *Eng. Failure Anal.*, vol. 119, Jan. 2021, Art. no. 104958, doi: 10.1016/j.engfailanal.2020.104958.

[20] M. Sharma, P. Verma, and L. Mathew, "Design an intelligent controller for a process control system," in *Proc. Int. Conf. Innov. Challenges Cyber Secur. (ICICCS-INBUSH)*, Feb. 2016, pp. 217–223, doi: 10.1109/ICICCS.2016.7542302.

[21] M. K. Bhaskar, N. S. Pal, and V. K. Yadav, "A comparative performance analysis of automatic generation control of multi-area power system using PID, fuzzy and ANFIS controllers," in *Proc. 2nd IEEE Int. Conf. Power Electron., Intell. Control Energy Syst. (ICPEICES)*, Oct. 2018, pp. 132–137, doi: 10.1109/ICPEICES.2018.8897477.

[22] J. J. Macías-Hernández, P. Angelov, and X. Zhou, "Soft sensor for predicting crude oil distillation side streams using evolving Takagi-Sugeno fuzzy models," in *Proc. IEEE Int. Conf. Syst., Man Cybern.*, 2007, pp. 3305–3310, doi: 10.1109/ICSMC.2007.4413939.

[23] F.-J. Chang and Y.-T. Chang, "Adaptive neuro-fuzzy inference system for prediction of water level in reservoir," *Adv. Water Resour.*, vol. 29, no. 1, pp. 1–10, 2006, doi: 10.1016/j.advwatres.2005.04.015.

[24] L. A. Zadeh, "From computing with numbers to computing with words-from manipulation of measurements to manipulation of perceptions!" *Adv. Soft Comput.*, vol. 6, no. 1, pp. 3–37, 2000, doi: 10.1007/978-3-7908-1841-3_1.

[25] Y. Dote and S. J. Ovaska, "Industrial applications of soft computing: A review," *Proc. IEEE*, vol. 89, no. 9, pp. 1243–1265, Sep. 2001.

[26] A. Nevado, L. M. Oñate, J. Sanz, R. Alcalde, and K. Slaven, "Temperature optimization of a naphtha splitter unit," *Adv. Electr. Comput. Eng.*, vol. 8, no. 1, pp. 7–16, 2008, doi: 10.4316/aece.2008.01002.

[27] A. Al-Jlibawi, M. L. B. Othman, M. S. Al-Huseiny, I. B. Aris, and S. Bahari, "The efficiency of soft sensors modelling in advanced control systems in oil refinery through the application of hybrid intelligent data mining techniques," *J. Phys., Conf. Ser.*, vol. 1529, no. 5, May 2020, Art. no. 052049, doi: 10.1088/1742-6596/1529/5/052049.

[28] S. K. Gharghan, R. Nordin, A. M. Jawad, H. M. Jawad, and M. Ismail, "Adaptive neural fuzzy inference system for accurate localization of wireless sensor network in outdoor and indoor cycling applications," *IEEE Access*, vol. 6, pp. 38475–38489, 2018, doi: 10.1109/ACCESS.2018.2853996.

[29] Z. Pawlak, "Rough sets wojciech ziarko," *Rough Sets*, vol. 38, no. 11, pp. 89–95, 2006.

[30] A. Al-Jlibawi, I. M. L. Othman, M. S. Al-Huseiny, I. B. Aris, and S. B. M. Noor, "Efficient soft sensor modelling for advanced manufacturing systems by applying hybrid intelligent soft computing techniques," *Int. J. Simul., Syst., Sci. Technol.*, vol. 19, no. 3, pp. 15.1–15.7, 2018, doi: 10.5013/IJSSST.a.19.03.15.

[31] D. F. Ahmed and M. Y. Nawaf, "Design of multivariable control system of a distillation tower via simulation using MATLAB/simulink," *Tikrit J. Eng. Sci.*, vol. 26, no. 3, pp. 51–61, Nov. 2019, doi: 10.25130/tjes.26.3.07.

[32] E. A. Jalee and K. Aparna, "Neuro-fuzzy soft sensor estimator for benzene toluene distillation column," *Proc. Technol.*, vol. 25, pp. 92–99, 2016, doi: 10.1016/j.protcy.2016.08.085.

[33] M. R. Serpas, "Soft sensors for process monitoring of complex processes," Ph.D. dissertation, Mitchell Roy Serpas, Graduate Stud. Texas A&M Univ., 2012.

[34] M. Lutfi and I. Aris, "Inconsistent decision system: Rough set data mining strategy to extract decision algorithm of a numerical distance relay—Tutorial," in *Advances in Data Mining Knowledge Discovery and Applications*, 2012, doi: 10.5772/50460.

[35] M. L. Othman, I. Aris, M. R. Othman, and H. Osman, "Rough-set-based timing characteristic analyses of distance protective relay," *Appl. Soft Comput. J.*, vol. 12, no. 8, pp. 2053–2062, 2012, doi: 10.1016/j.asoc.2012.03.004.

ALI HUSSEIN HUMOD AL JLIBAWI (Member, IEEE) received the B.Sc. degree in control and system engineering/process control engineering from the University of Technology (UoT), Baghdad, Iraq, in 2004, and the master's degree in manufacturing systems engineering from Universiti Putra Malaysia (UPM), Serdang, Malaysia, in 2015, where he is currently pursuing the Ph.D. (Doctor of Philosophy) degree in control system engineering with the Department of Electrical and Electronics Engineering, Faculty of Engineering. He is also a Research Member of the Advanced Lightning, Power and Energy Research (ALPER), UPM. He also practices as a Manufacturing Process Engineer in private industries sector works in Iraq design and project administration consultancy. His research interests include, among others, process control systems in manufacturing systems, computational-intelligence-based data mining for knowledge discovery in manufacturing database, application of artificial intelligence in soft sensors, image processing strategies in industries systems, and development of process control systems in oil refinery by applying machine learning techniques.

MOHAMMAD LUTFI OTHMAN (Senior Member, IEEE) received the B.Sc. degree *(magna cum laude)* in electrical engineering from the University of Arizona (UofA), Tucson, Arizona, USA, in 1990, and the M.Sc. and Ph.D. degrees in electrical power engineering from Universiti Putra Malaysia (UPM), Serdang, Malaysia, in 2004 and 2011, respectively. He is currently an Associate Professor with the Department of Electrical and Electronics Engineering, Faculty of Engineering, UPM, where he is also a Research Member of the Advanced Lightning, Power and Energy Research (ALPER). He also practices as an Electrical Engineering Consultant in electrical services installation works by diversifying as the Electrical Director/a Partner in a local engineering consulting firm. He is also a Professional Engineer with Practicing Certification (PEPC) registered under the Board of Engineers Malaysia (BEM), a Chartered Engineer (CEng) registered under the Engineering Council U.K., a Professional Technologist (PTech) registered under the Malaysian Board of Technologists, a Registered Electrical Energy Manager (REEM) under Energy Commission Malaysia and a Certified Professional in Measurement and Verification (CPMV) under Malaysian Green Technology Corporation. His research interests include, among others, power system protection (protective relay operation modeling and analysis, computational-intelligence-based data mining for knowledge discovery in relay database, application of artificial intelligence in protection algorithms, adaptive numerical protective relays, development of numerical protective relays), power system operation (power quality, smart grid, distributed generation), electrical services installation works (design and project administration consultancy) and energy efficiency management (demand side management, energy efficiency management, and building energy management systems).

ARIS ISHAK received the B.Sc. degree from George Washington University, USA, in 1988, and the Ph.D. and M.Sc. degrees from the University of Bradford, U.K., in 1995 and 1991, respectively. He is currently a Professor with the Department of Electrical and Electronic Engineering, Universiti Putra Malaysia. His research interests include artificial intelligent, vehicle communication systems, power electronics & drives systems (electric & hibrid vehicles), robotic systems, renewable energy systems, automotive power train engine management systems, and IoT systems.

BAHARI S. MOH NOOR, photograph and biography not available at the time of publication.

AL HUSEINY M. SATTAR SAJITT received the B.Sc. and M.Sc. degrees in computer and software engineering form AL-Mustansiriya University, in 2002 and 2005, respectively, and the Ph.D. degree in electronics and computer science from the University of Southampton, U.K., in 2012. He received several research grants and a study scholarship. He is currently an Alumnus of the Fulbright Visiting Scholars Program with the University of Central Oklahoma, in 2014. He is also a Faculty Member of the College of Engineering, Wasit University. He published several research papers in these fields and authored a book in cryptography. His current focus is on developing wearables for medical diagnosis by using machine learning. His research interests include computer vision, machine learning, biomedical engineering, the IoT, and cryptography.