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Adaptive Fuzzy Controller for Loop Control in a Distributed Control System

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Abstract— **to simplify the control task and reduce the computation burden of control system, Distributed Control system (DCS) becomes the most suitable control system structure especially for medium and large size of industrial processes. In DCS system the control task is distributed among some controllers, which communicate to each other via communication network, such as PLC or/and industrial PC. In most DCS system, each controlled variable is manipulated in an individual loop, which is called control loops in DCS. Since it is difficult to design a control function that can handle all the circumstances of operations at the start phase, the control function needs to be adapted online. Adapted fuzzy controlled is suggested here in order to handle the control loops of a DCS system. An Experimental setup simulates the master loops of Liquefied Petroleum Gases (LPG) subsystem in a refining petroleum industry. The controller is implemented using HP-VEE software and Matlab packages.**

KEY WARDS: *LPG, DCS, ADAPTIVE CONTROLLER, NORMALIZED FUZZY CONTROLLER*

I. INTRODUCTION

SINCE many industrial processes are of a complex nature, it is difficult to develop a dynamic model that can describe the system behavior. The complexity of industrial processes requires high capabilities of control system. Therefore, the DCS is considered as the most popular control system for such type of processes. Moreover, it is so difficult to control the whole system variables altogether. As a consequence, most of DCS divides the process into some of control loops for each individual variable. On the other side, the human operator is often required to provide on line adjustment for control loop, which makes the process performance greatly dependent on the operator experience.

Most of the control loops in DCS suffer from many unexpected disturbances, noise and parameter variations. Thus, the human supervision could not fulfill the required performance especially when the operator has less experience. Less experience of operator may cause degraded performance and some times may cause failure and loss of production. [1], [4]. Therefore, self tuning of a control loop parameters is an essential demand for most DCS loop in industrial process.

The LPG recovery process is a subsystem existing in the majority of petrochemical industries. The LPG recovery process is a multi-input/output process, PID controller is the main controller used to control its loop variables. The process is affected by unexpected conditions, which makes the controller fails to maintain the process variable performance within the accepted limits. The coupling between the different loops such as the effect of level loop on pressure loop has a great effect on the loop performance. Retuning the controller, in such cases, is mandatory in order to recover the required performance. The process configuration, operation and control will be described in the next section.

Conventional control techniques, such as PID, have some drawbacks especially to deal with the nonlinearities, constraints, uncertainties,…, etc. which make the new approaches mainly Artificial Intelligent (AI) [2] techniques are very important. These approaches were practically appealing because of their ability to capture nonlinearities. During 1990s, these approaches found their way into commercial control applications.

Fuzzy controller is one of AI techniques that have a great use in the industrial application because of its ability to emulate the human thinking. Although a static fuzzy controller reflects the experience of the process operator, it has not the abilities to handle process situations or variations that have not been considered during fuzzy controller design. Hence, continuous adapting of fuzzy controller is necessary [2], [3], [13], [15] and [16] in order to handle the process variations and recover the process performance. Adaptive fuzzy controller is suggested here to adapt normalized fuzzy controller, mainly output/input scale factor. Due to the difficulties to direct implement the suggested technique on the real process, the algorithm is tested on an experimental setup, which simulates two master loops of the LPG unit namely level and temperature loops. A comparison between scale factors adjustment and classical adaptation method are done. The suggested control algorithm consists of two controllers: process variable controller (normalized fuzzy controller) and a supervisory controller to adjust the scale of the normalized controller. Normalized fuzzy controller is explained in [3], [4], and [10] and the previous methods of scale factor selection are discussed in [3]-[7]. The priorities of input or output scale factors selection are introduced in [8].

In the second section of this paper, the LPG recovery process and its control problem are presented.

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Adaptive fuzzy controller, which is suggested to control the DCS loops of LPG subsystem, is highlighted in section III. Section IV illustrates the experimental setup hardware and software configuration and in addition to some results for the two master loops of LPG. The conclusion and results discussion is introduced in the last section.

I. LPG RECOVERY PROCESS AND PROBLEM STETMENT

LPG is a light saturated paraffin hydrocarbon derived from the refinery process of crude petroleum oil stabilization and natural gas processing plants. It consists mainly of propane (C3H8) and butane (C4H10) or a combination of both with some other hydrocarbons. It is liquefied under pressure for transportation and storage.

The LPG recovery process is to separate the main components of LPG, which are C3H8, C4H10 and the other hydrocarbons. The separation takes place at a certain heating temperature. One of the LPG recovery process, in ANRPC Petroleum Company in Egypt, starts by Deethanizer (Ethan separation C2H6) process followed by Depropanizer and Debutanizer process.

The schematic Diagram of the Deethanizer recovery process is shown in Fig.1. Treated LPG is feed to the upper of the separation tower and the outlets of the tower are Ethan and treated LPG. The Ethan produced is collected in dram receiver, the receiver has a level controller to control Ethan level in the receiver and if the level increase over the limits some of the condensate Ethan is feedback to the deethanizer tower.

The Deethanizer Recovery process requires a certain conditions of temperature, level and pressure. Each process variable (Temperature, Level and Pressure) in the recovery process is controlled by an individual control loop in the DCS. PI controller is the main controller for these control loops. The level of LPG in the Deethanizer tower is controlled based on the second stage (Depropanizer and Debutanizer) demand and the utility required as in Fig.1. The temperature of Ethan produced is controlled through deethanizer reboiler by changing the steam flow rate to the reboiler. The pressure is a dependent variable affected by the level and temperature.

In this process, the Ethan temperature must be maintained at 420^{o}c all the time. The heating of LPG is performed using steam. The process temperature is controlled by adjusting the inlet steam and outlet condensed water flow rate to and from the reboiler unit as in Fig.1. Because of the variation of steam condition (pressure and temperature) during operation, the temperature controller could not maintain the temperature around the allowable range 420^{o}c ± 2%. Hence, a human supervision plays an important roll by tuning the loop controller in order to maintain the performance within the accepted limits. The efficiency of the human supervision is based mainly on the human experience.

This type of process is a continuous and complex process. Therefore, the conventional controller cannot handle all situation of the process. This makes a supervisory controller is essential to adapt the controller parameters. Moreover, the controller used in such process must be fast and simple because of the huge number of controlled variables in order to reduce the computational burden.

The AI control technique needs to well known by the process operation (experience) in order to construct/learn the controller of the process variables. Since different process situations may take place during the operation regardless during controller construction and start up, the adaptation method is also necessary even if the AI controller is used [2].

Thus, an adaptive controller with some experience about the process and without knowing actual process model is preferred to adjust the performance in the majority of process situations and reduce the human supervision effort.

An adaptive fuzzy controller is suggested to control and adapt most of single input/output DCS loop. This algorithm is tested on an experimental setup, which simulates a small model for the deethanizer LPG recovery process. The control algorithm is implemented on the temperature and level loops of LPG unit.

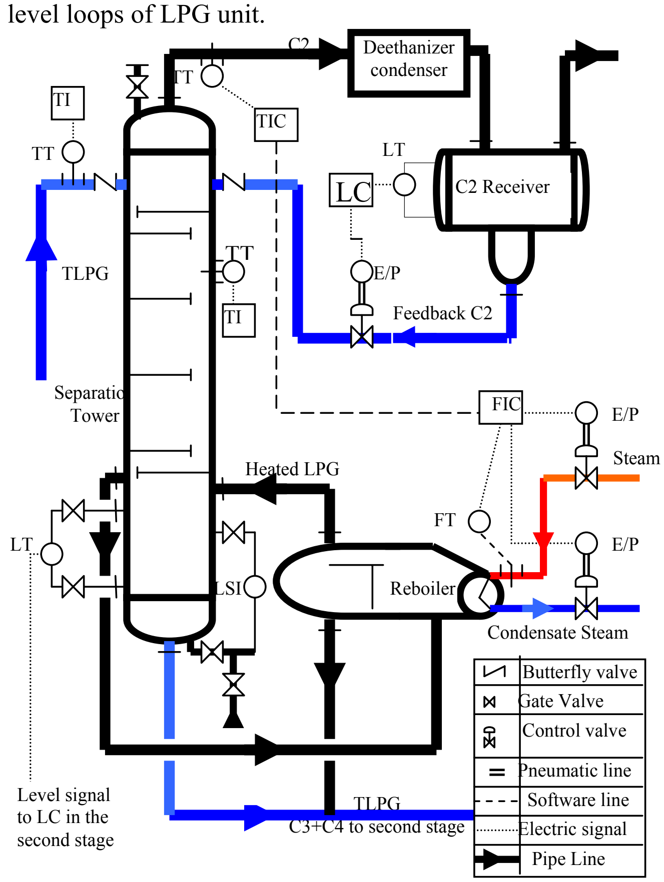

Fig. 1 Schematic diagram of Deethaniyer LPG recovery process

II. ADAPTIVE FUZZY CONTROLLER

A. NORMALIZED FUZZY CONTROLLER

To overcome the problem of PID due to the disturbance and parameter variation, a normalized Fuzzy controller with adjustable scale factors is suggested. The normalized fuzzy has two crisp inputs and one crisp output. The input variables represent the error and rate of error of the manipulated variable of the control loop. While, the output variable represents the control signal. In the experimental case study, the fuzzy controller designed has the following parameters:

- Membership functions of the input/output signals have the same universe of discourse equal to 1
- The number of membership functions for each variable is 5 with triangle membership functions denoted as NB (negative big), NS (negative small), Z (zero), PS (positive small) and PB (positive big) as shown in **Fig. 2** Fuzzy allocation matrix (FAM) or Rule base as in Table1.
- Fuzzy inference system is Mamdani with "centroid" for Defuzzification.

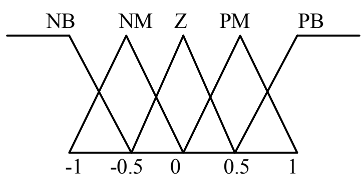

Fig. 2 Normalized membership function of inputs and output variables

Table 1 FAM of normalized fuzzy controller

e \ Δe	NB	NM	Z	PM	PB
NB	PB	PB	PM	Z	Z
NM	PM	PB	PM	Z	Z
Z	PM	PM	Z	NM	NM
PM	Z	Z	NM	NB	NB
PB	Z	NM	NB	NB	NB

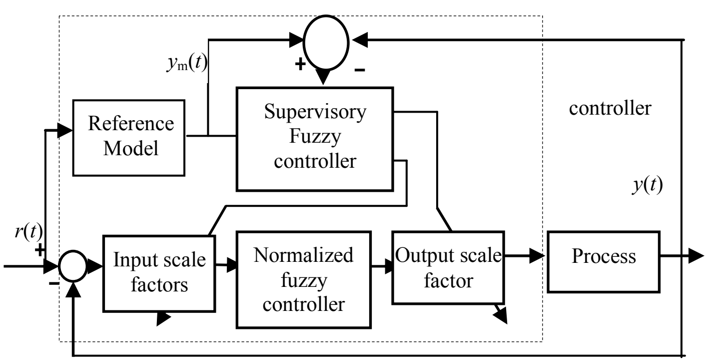

Fig. 3 Over-all Block diagram of supervisory fuzzy controller

Fig. 3 shows the block diagram of supervisory fuzzy controller. The scale factor of the normalized fuzzy controller determines the range of universe of discourse of the input and output variable of fuzzy controller [10]. As shown in **Fig. 3**, the input and output scale factors are adapted using another fuzzy controller called supervisory fuzzy controller based on the error between the reference model output and the process loop output.

B. FUZZY SUPERVISIOR AND ADAPTATION

The adjustment of the scale factors of the input and the output of the normalized fuzzy controller can be achieved using adaptive mechanism such as Gradient Decent (GD) adaptation [4], [9]and [11]. The adaptation mechanism seeks to decrease the value of the quadratic objective function based on the instantaneous error

$e(k)$: $J(k) = 1/2\, e^2(k)$. (1)

The error here is a plant output error e_y

$$e_y(k) = y_m(k) - y(k). \quad (2)$$

The performance index will be:

$$J(k) = \frac{1}{2}\left(y_m(k) - y(k)\right)^2 \quad (3)$$

Where:

$y_m(k)$ is the reference modeled output.
$y(k)$ is the actual output.

The parameter set, θ, of the fuzzy scale factors is changed via the following iterative adaptation rule:

$$\theta(k+1) = \theta(k) + \Delta\theta(k) = \theta(k) - \alpha\, \partial J(k)/\partial\theta(k) \quad (5)$$

Where α is the adaptation parameter, θ *is the scale factor.*
According to the GD techniques [4], [9]and [11] the derivative term will be:

$$\partial J(k) / \partial\theta(k) = e\; \partial e(k) / \partial\theta(k) \quad (6)$$

then

$$\theta(k+1) = \theta(k) + \Delta\theta(k) = \theta(k) - \alpha\, e\; \partial e(k) / \partial\theta(k) \quad (7)$$

This technique is implemented for output scale factor adaptation, while for input scale factor is difficult to implement.

The adaptation of the scale factor as in Fig. 3, is a supervisory fuzzy controller. In this method, a supervisor fuzzy controller is designed to change the scale factors on line. The design of the supervisor fuzzy controller can be constructed by two methods:

a) Learning method [1], [2], [11], [16]
b) Experience of the system and main requirements must be achieved.

In this work, the supervisor controller is built according to the accumulative knowledge of the previous tuning methods.

The supervisor fuzzy controller has the following parameters:

- the universe of discourse of input and output is selected according to the maximum allowable range and that is depend on the process requirements
- The number of membership functions for input variables is 3 triangle membership functions denoted as N (negative), Z (zero), and P (positive). For output variable is 2 membership functions denoted as L (low) and H (high) as shown in Fig. 4. The allocation matrix (FAM) or Rule base as in Table 2.

- Fuzzy inference system is Mamdani with "centroid" for Defuzzification.

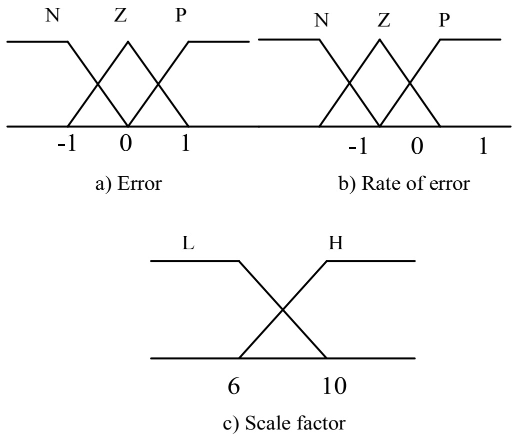

Fig. 4 Membership Function of inputs and output of supervisory fuzzy controller

Table 2 FAM of supervisory fuzzy controller

E \ Δe	N	Z	P
N	H	H	L
Z	L	L	H
P	L	H	H

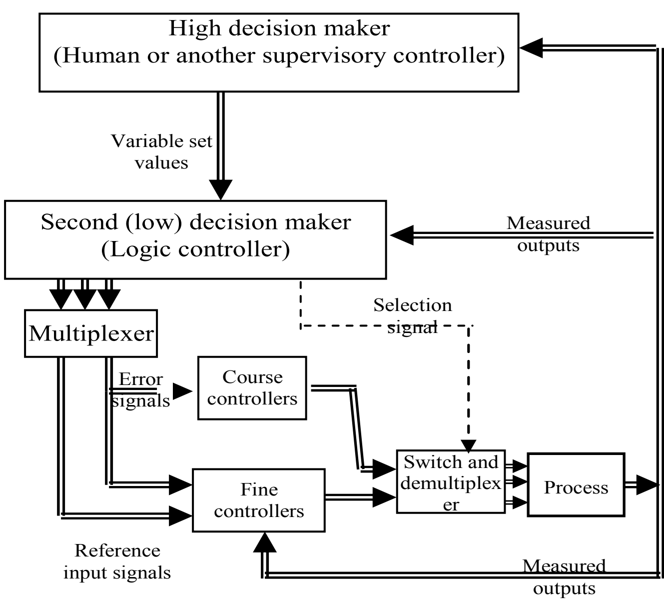

Fig. 5 Over-all Block of self adapted supervisory fuzzy controller for multivariable system

The overall block diagram of the system with supervisor controller is shown in Fig. 5. The loop variables are controlled using two controllers, fine and course one. The course controller is used when the process variable is considerably far from the desired value using a normalized fuzzy controller without adaptation. While the fine controller is used to make fine adjustment using adaptive fuzzy controller illustrated in Fig. 5.

C. *UNIVERSE OF DISCOURSE SELECTION*

The previous control structure is a general controller for different loops in DCS, especially LPG process. According to the previous algorithm, for any single-input/output process, there are three universe of discourse must be determined: error; rate of error; control signal.

1- Universe of Discourse of Output Scale Factor

The output scale factor is determines the range of control signal. It is selected based on the maximum control signal range u_{max}. If the controller is bidirectional (±) then the maximum universe of discourse changes from $-u_{max}$ to $+u_{max}$. While if the controller is unidirectional (+) then the maximum universe of the controller output range 0-u_{max} and the output signal is calculated from the following equation:

$$u_o=u_{max}+s_o*u_f \qquad (8)$$

where u_o is final control signal; u_{max} is maximum allowable control signal; u_{min} is minimum allowable control signal; s_o is output scale factor; u_f is normalized fuzzy output.

2- Universe of Discourse of Input

The input scale factors determine the range of the error and the rate of error for each controlled variable. As shown in Fig. 5, the process operates in two modes: proportional (course) mode; supervisory (fine) mode.

i. Course mode: the controller operates in this mode in two cases. First; when the reference input changes from step to another. Secondary; when the error reaches predetermined value based on the specification of the allowable error required from the system decided by the main supervisor (Human or other supervisory controller in Hierarchal system). The controller output in this case is maximum allowable value and the rate of error change is calculated continually in this period according to the following equations:

$$e(k)=y(k)-r(k) \qquad (9)$$

$$\Delta e(k)=(e(k)-e(k-1))/T \qquad (10)$$

where y(k) is the actual output; r(*k*) is the reference input; e(k)is the error at sampling instant k; Δe(k) is the rate of error at sampling instant k; T is sampling time.

Record e(k) and Δe(k) until the error reaches a certain values determined by the main supervisor. The courses are calculated from the following equations:

$$U_e=1/e_{max} \qquad (11)$$

$$U_{\Delta e}=1/\Delta e_{max} \qquad (12)$$

where e_{max} is the maximum allowable error required; Δe_{max} is the maximum rate of error calculated during the proportional mode.

ii. Fine mode: in this case the calculated values of the universe of discourse of the inputs and outputs scale factors are used in supervisory fuzzy. The switching from course to fine mode is depending on the value of maximum allowable error between the actual and reference input, which is predetermined by the main supervisory.

According to the above analysis of scale factors universe calculations, there are two decision makers in the control system rather than the control algorithm suggested as shown in Fig. 5. The first decision maker is the main (global) supervisor (human or another supervisory controller) which decide the main set values of the process variable (maximum and minimum value of controller output, minimum and maximum allowable error, etc.). The second one is a logical controller which switches between the course and fine controller and computes the universe of discourse of input and output based on the set values of the of the main supervisory. In this case one supervisor controller can handle more than one process variable where the sampling time for supervision is smaller than the sampling time of the process variable. Hence, each group of process variables are supervised by one supervisory controller the selection between them is achieved using multiplexer at the input of the supervisory and de-multiplexer at the outputs.

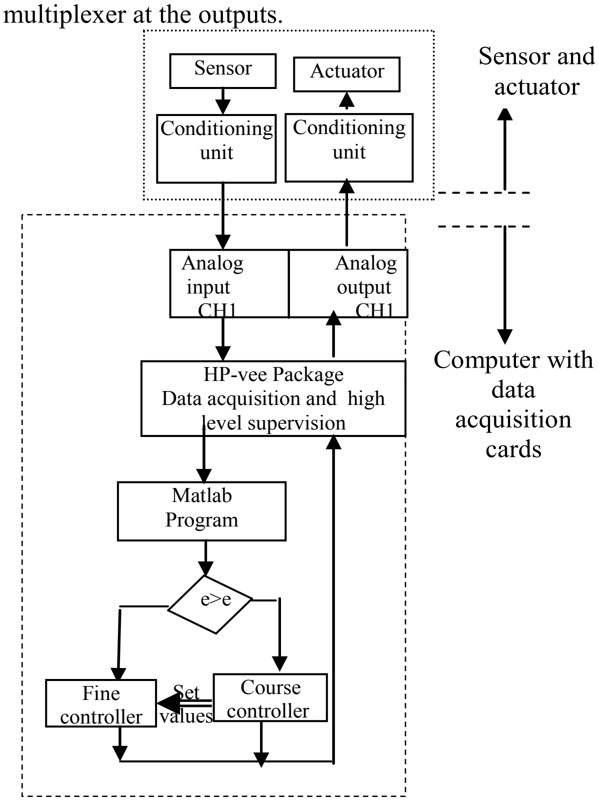

Fig. 6 The flow chart of self adjusting supervisory controller of experimental level process.

III. PRACTICAL RESULTS

As described before, two loops are tuned, temperature and level loops. Each loop is manipulated according to the flow chart shown in **Fig. 6**. The physical signals are measured using data acquisition card. HP-VEE package is used as a data acquisition system and high supervisor controller. The fuzzy controller is implemented using Matlab package. The control signal is calculated using Matlab. The Matlab package communicates with HP-VEE package using a special communication protocol in HP-VEE. In the real process, the required temperature has to be around 420^{o}c while in the experimental setup the temperature is reduced to be around 60^{o}c due to the limitation of experimental setup. Both temperature and level loops suffer from disturbances. The disturbance in temperature loop is simulated by changing the water flow rate. In addition, the disturbance in level loop is simulated by changing the discharging valve.

A. Hardware Configuration

In the experimental setup, the system hardware used is a Personal Computer (PC) containing a data acquisition card type DAS08 form HP company. The analog signals of temperature and level is collected in HP-VEE package.

B. Software Configuration

As discussed before, the software used is the HP-VEE as the supervisory interface and Matlab to implement the control function, mainly Fuzzy and adaptive fuzzy.

Fig. 7 shows the interface screen of HP-VEE, which represent the HMI (Human Machine Interface) between the system and operator. In addition, **Fig. 8** illustrates the programming techniques of HP-VEE.

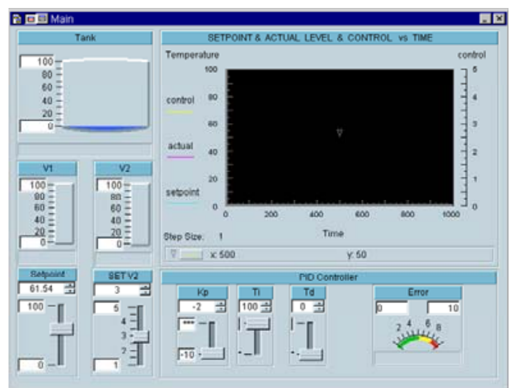

Fig. 7 Interface screen of HP-VEE

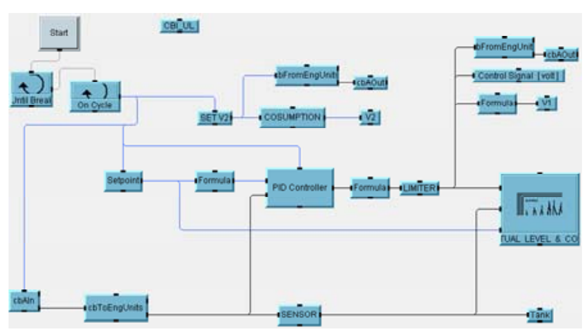

Fig. 8 Programming screen

Fig. 9 shows the temperature response using supervisory fuzzy controller by adapting both input and output scale factors. The response shows the robustness of supervisor fuzzy tuning both input and output scale factor. In this response, the feeding water flow rate changes during the operation, which equivalent to steam variation in LPG recovery process. Flow rate is changed from 0% to 75%, where 100% flow rate means 2litre/min.

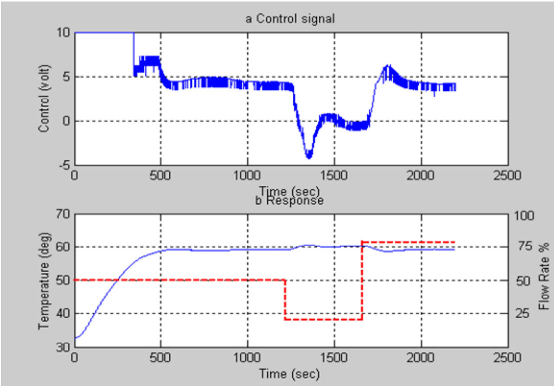

Fig. 9 Control signal and output temperature for flow rate disturbance

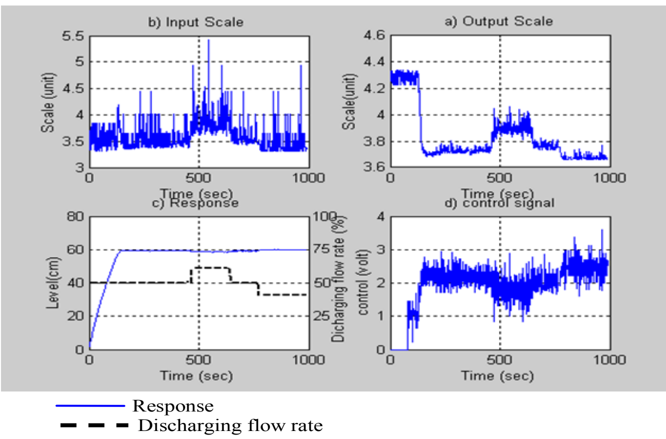

Fig. 10 Level response for step 60 cm and disturbed discharging flow rate

The supervisor fuzzy controller, here, is a multi-input multi-output fuzzy controller without coupling between the variables, i.e. the same supervisor algorithm is applied to each output individually with different universe of discourses.

The required performance of temperature is represented by a reference model and the system should follow the required response (overshoot, rise time, etc.). The desired specification of the system response is chosen to be: overshoot$\leq$ 20%; rise time $\leq$ 150s. the desired specification is described by equation (12).

$$y_d(t)=A*[\,1-1.59\,e^{-0.488t}\sin(0.3929t+38.83*\pi/180)] \qquad (12)$$

where A: step required.

The second control loop is the level of LPG in the Deethanizer tower based on the second stage (Depropanizer and Debutanizer) demand and the utility required as in Fig. 1. by Adjusting the output/input scale factors range of the supervisory controller and test the overall system for step input equivalent to 60cm and the outlet valve adjusted to 50% open. The controller structure, here, is as in the temperature case, but the difference is only the range of scale factor the fuzzy controllers. The system response and scale factor variation, with variable discharging flow rate from 50, 60,50 to 40, are shown in Fig. 10. The result of the level process responses shows that the suggested algorithm is suitable to most of process variables in the DCS with small efforts on the main supervision.

IV. Conclusion

LPG recovery process is an important subsystem in most of refining petroleum industries. It is a multi-input/output process and PI controller is the main controller used to control the most of process variables. Process is frequently exposed to unexpected conditions in addition to the coupling between different loops. Hence, the PI controller fails to maintain the process variable in satisfied conditions and it is necessary to retune the controller. Supervisory fuzzy controller is suggested here to adapt normalized fuzzy controller, mainly output/input scale factors. The algorithm is tested on an experimental model, which simulates the main two loops in LPG unit, temperature and level loops. The control algorithm can be applied for any multi-input/output system as multi-loops of single-input/output loop (Decoupling). This method also seems to be simple to implement, systematic, and has a less computational burden.

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