A Bio-Inspired Robust Controller for a Refinery Plant Process

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Abstract. This research presents a novel bio-inspired knowledge method, based on gain scheduling, for the calculation of Proportional-Integral-Derivative controller parameters that will prevent system instability. The aim is to prevent a transition to control system instability due to undesirable controller parameters that may be introduced manually by an operator. Each significant operation point in the system is firstly identified. Then, a solid stability structure is calculated, using transfer functions, in order to program a bio-inspired model by using an artificial neural network. The novel method is empirically verified under working conditions in a real refinery plant process.

Keywords: bio-inspired models, artificial neural networks, knowledge-based system, industrial applications, robust stability.

1 Introduction

For various reasons there are very few companies that provide industrial products to monitor industrial processes in the context of oil refineries. It may be said that a common characteristic of the different alternatives in existence is that they are closed to possible modifications. The monitoring technologies that they incorporate are usually conventional, and the operators therefore require no ongoing training and updating. Thus, it is necessary that the improvements should aim to complement the monitoring and control applications with which the operators are fully familiar.

In general, continuous research is necessary in the field of process engineering to arrive at new methods of regulation, in order to improve current designs [1]. The demand for system control applications is driven by the increasingly numerous ranges of possibilities [2-8] that are nowadays under development or in use.

Despite the rapid development of novel methods for regulation processes, better alternatives to popular techniques, such as the 'conventional' Proportional-Integral-Derivative (PID) controller, have yet to be found. Many aspects of PID have been examined, ever since the first theoretical analysis of a PID controller by Nicholas Minorsky [9] in 1922.

This study introduces a neural network to prevent control system instability that is regulated using gain scheduling with predetermined PID coefficients. The method is validated on a real process of a refinery. Numerous innovations have been introduced to control systems for processes in almost all fields [10, 11]. Interesting examples are those based on artificial intelligence methods, [5-8, 12]. Nevertheless, the vast majority, as many as 90% [13], of control loop systems use PID controllers. Nowadays, conventional PID is often applied for different reasons such as ruggedness, reliability, simplicity, error tolerance, and so on [14].

When dealing with non-liner systems, certain specifications have to be equal in all areas of operation. The regulator will therefore require different parameters for each area.

These problems can be reduced by using self-regulating and adaptive PID controllers [15, 16]. It should be noted, however, that their implementation can be expensive and specific to the type of process that it is meant to regulate, which further complicates any general theory on PID controllers.

Many of the drawbacks resulting from self-regulating and adaptive PID controllers are alleviated using the well-known Gain Scheduling method [17, 18]. This method is easier to implement, and normally achieves highly satisfactory results. The concept of Gain Scheduling began in the early 90s [19] and is now considered part of the family of adaptive controllers [15].

Significant system variables that define the point of operation have to be selected in order to implement Gain Scheduling. It is then necessary to choose several regions throughout the entire operating range of the plant, in which behaviour is linear. The controller parameters are then fixed which provide similar specifications for the operating range of the plant.

Although, there is no systematic procedure for these tasks; the first step often begins with the easily measured variables. The second step is more complicated, as it is necessary to choose operation points throughout the entire range of plant operations. The system may be stable for controller parameters that are deduced, but it may not be stable between the selected points. There is no simple solution to this situation, which is usually broken down into constituent parts. This is the reason why the subject has been studied by researchers [20, 21] and why it is necessary to create a Knowledge Base System (KBS) [22-27].

The Gain Scheduling method selects the correct controller parameters, although operators often adjust the parameter values with the aim of improving plant specifications. At times, the parameters they assign can cause instability. The novel bio-inspired method proposed in this study is intended to prevent instability. Among others, artificial neural networks are proposed as a means of overcoming the problem [28-35]. Essentially this method decides whether PID parameters programmed by human operators are valid and, whenever the plant enters an unstable zone due to parameter combinations, the method restores a more stable combination for the operation point in question.

This study starts with a brief introduction to PID controller topology in Section 2. Section 3 introduces the novel bio-inspired controller topology, and Section 4 goes on to explain the stability/instability solid structure concept. A case study based on a non-linear process in a real process of a refinery plant is used to demonstrate the proposed method. This is described in Section 5. Finally, the conclusions and future lines of work are presented in Section 6.

2 Controller structure

There are multiple ways to represent PID controllers, but perhaps the most widely used is given in equation 1, (commonly known as the standard format) [13, 14].

$$u(t) = K\left[e(t) + \frac{1}{T_i}\int_0^t e(t)dt + T_d\frac{de(t)}{dt}\right] \tag{1}$$

Where '*u*' is the control variable and '*e*' is the control error given by '*e* = *SP* – *y* (difference between '*SP*', the reference specified by the input and '*y*', the measurement unit specified by the output). The other terms are the tuning controller parameters: proportional gain '*K*', integral gain '*Ti*' and derivate gain '*Td*'.

3 A Novel Bio-Controller Knowledge Base System

System dynamics change with process operation conditions. Changes in a dynamic process may, for instance, be caused by well-known nonlinearities inherent in the system. It is possible to modify the control parameters, by monitoring their operating conditions and establishing rules. The methodology comprises the following steps: first of all, Gain Scheduling is applied, then the behaviour of the plant is analyzed at different points of interest, and, finally, rules are established to program gains in the controller. It would then be possible to obtain certain specifications which remain constant throughout the whole range of operation. In the novel proposed method, it is possible to change the PID parameter values to improve the operating conditions, but the possibility of undesirable parameter combinations must be prevented. This idea is schematically represented in Figure 1.

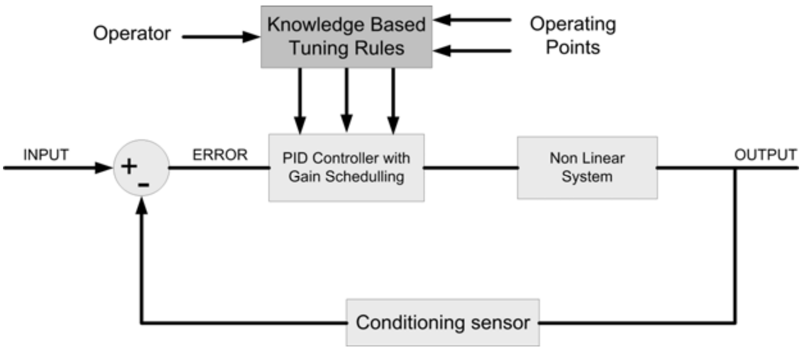


Figure 1. Gain Scheduling with proposed topology

The idea of Gain Scheduling is to obtain the PID parameters when given the operating points. In this case, a new input has been added, with which the operator can modify the other parameters taken from knowledge-based tuning rules. Figure 2 shows a basic diagram of the suggested structure for the method in which PID parameters may be adjusted by the operator. If the input causes system instability, the proposed topology can commute parameters and program the controller to maintain it within the dynamic range of the plant.

There is a Multilayer-Perceptron (MLP) [36] in the proposed system, which must be trained to detect the existence of stable parameter combinations. In case of instability, the system will revert back to stable values according to the initially programmed operating work point.

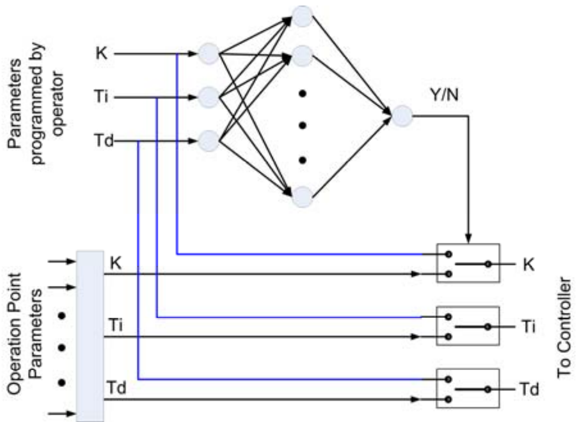


Figure 2. Multi-Layer Perceptron Neural Network architecture

4 Stability structures definition

In order to apply a MLP network, an interesting and informative data set must be chosen.

To that end, solid stability and instability structures were applied, in order to delimit both states in absolute terms. These structures are defined by PID controller parameters along with their stability/instability (both states do not coexist) points that have to be placed into three axes of a three-dimensional graph. Abundant literature exists on robust stability problems that describe this concept [37-39]. Figure 3 shows an example of a solid stability structure: a 3-dimensional graph (the three parameters of the controller K, Ti and Td) with the corresponding 2-dimensional views. The volume that is represented in the 3-dimensional graph consists of parameter combinations of the controller for a stable system. Were the structure unstable, then the volume would consist of the parametric controller combinations for an unstable system.

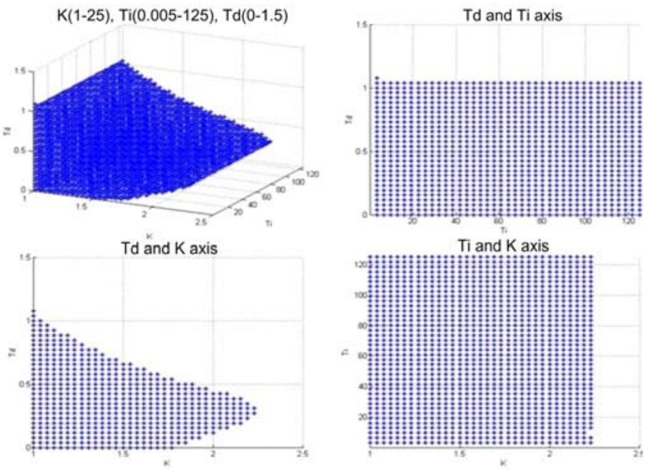


Figure 3. Example of a solid stability structure

5 Empirical verification of the novel proposed method

A general schematic diagram of the extraction process of a fraction of Heavy Gas Oil (HGO) from a crude oil distillation tower (DA-101) in a refinery is shown in figure 4.

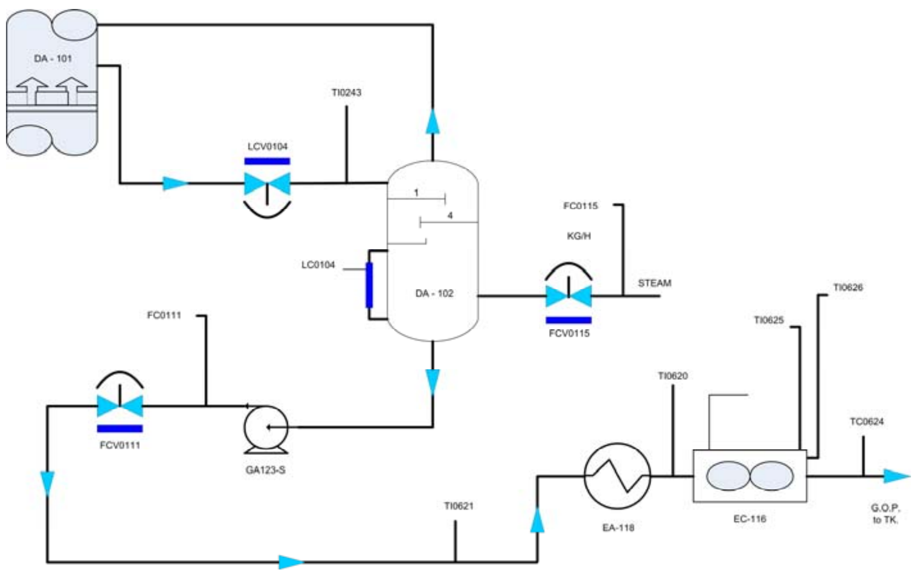


Figure 4. Schematic diagram of the process

Conceptually, the process may be divided into the phases that are described as follows.

5.1 Phase 1 – HCO extraction process from a distillation tower

Figure 5 shows a diagram (figure 4) that corresponds to this section.

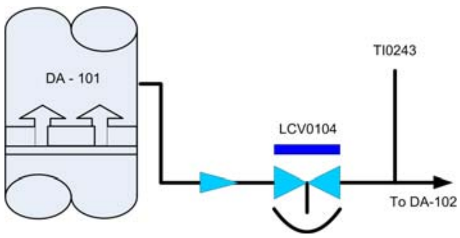


Figure 5. Diagram of Phase 1 of the process

In order to monitor extraction from the distillation tower (DA-101), the set temperature is controlled by means of a temperature sensor based on Thermopar TI0243. The temperature is fixed for ‘95% of distillation’ (laboratory temperature at which 95% of Heavy Gas Oil (HGO) is obtained by distillation from that which is present in the overall sample), also known as the extraction temperature of the HGO draw-tray.

Monitoring of this temperature is carried out by varying the opening of the servo-controlled valve LCV0104, thus, if a large amount of HGO is extracted, the temperature at TI0243 will increase thereby closing the value, and *vice-versa* if a small amount is extracted. The HGO that is extracted at this stage falls into a “Stripper” (DA-102) in which a refinement of the fraction takes place, the functioning of which is described in sub-section 5.2.

5.2 Phase 2 – Process to return lighter fractions in the extraction to the distillation tower

The general diagram that corresponds to this part is shown in figure 6.

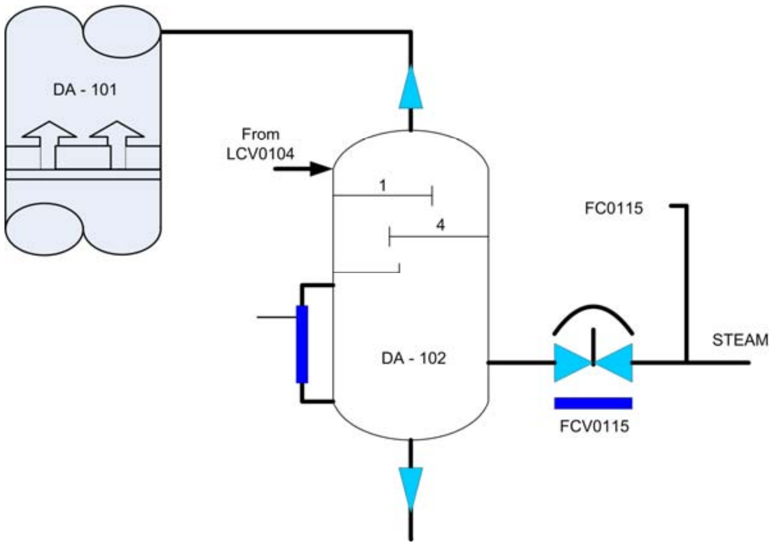


Figure 6. Diagram of Phase 2 of the process

The HGO from the earlier stage falls into the Stripper (DA-102). This is a recipient with internal trays in the upper half into which the product falls from above. When in operation, once the trays are full, stream is passed through it at low pressure reboiling it from below. The largest possible amount of steam is injected through controlled valve FCV0115, without losing the stability conditions of the plant. The pressure of the steam is approximately 4.5KG/cm^2, and the temperature is sufficient to avoid condensation. The purpose of this jet of steam is to extract the lightest fractions of HGO from the earlier stage and route them back to the upper part of the stripper in the distillation tower DA-101, where they are recovered in the fractions immediately above HGO. The flow to the distillation tower is possible given the pressure in the distillation column that is within a range of 0.25 to 0.9 KG/cm^2, in accordance with the characteristics of the load. It is important to maintain the pressure in the tower (DA-101), as if this is modified, it will also change the distillation temperature. Once refined, the HGO is stored in the lower half of the stripper and is drawn off from below by the process that is outlined in the following subsection.

Normally the purpose of using a stripper is to correct the inflammability point, however in the case of HGO this is not the objective. The HGO is a fraction that is somewhere between diesel, an important element from the commercial point of view and the atmospheric residue at the bottom of the tank from which other compounds are extracted. In this case, the purpose of the stripper is to draw off the maximum possible amount of HGO to the tank and the lighter fractions towards diesel.

5.3 Phase 3 – Pumping of the refined HGO fraction to the storage tanks

The diagram in figure 7 shows the process of pumping the refined HGO fraction to the storage tanks:

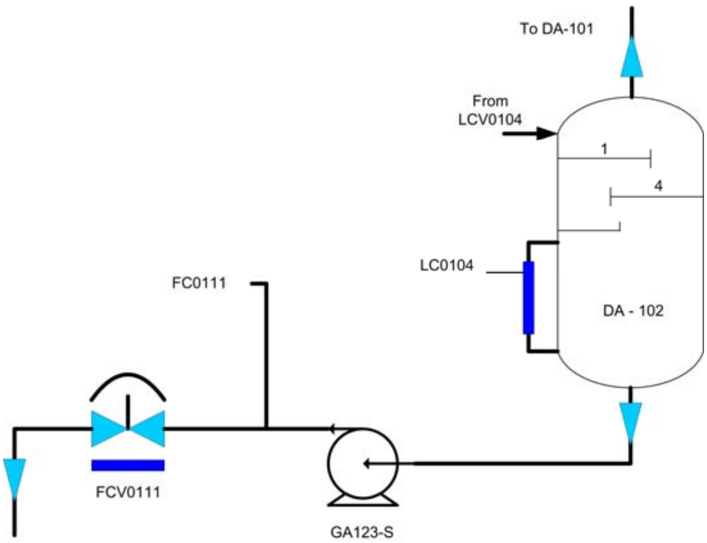


Figure 7. Diagram of Phase 3 of the process

There are no trays in the lower-half of the stripper (DA-102), where the refined GO from the upper part is stored before it is pumped to the tank GA123-S. The level of GOP existing in that area of the stripper is measured with a differential pressure level sensor LC0104.

A very important aspect is that the level of HGO has to be situated at a constant value within a range that is between 30% to 80% of the full capacity. It is not excessively important whether the value is at one or another end of the range, but only that it is not in a zone which would negatively influence the unit. The value has to be constant owing to the fact that the amount of steam that is introduced to extract the lighter fractions is constant and if the level of HGO varies the quantity of lighter fractions extracted and piped back to the distillation tower (DA-101) will also change and as a consequence the upper fractions, causing instability.

Control of the level is carried out by varying the opening of the servo-controlled valve FCV0111, such that if it is opened the reading level in the stripper will fall and if closed, it will rise. It is a difficult variable to maintain, as the amount of HGO that enters in the upper part will depend on the regulation of the valve that ensures a constant fraction (LCV0104). It is highly recommendable that as far as possible the aforementioned limits on the HGO level in the stripper are not exceeded, so that the operator has a margin for manoeuvre.

5.4 Phase 4 – Process to make use of HGO heat and cooling for storage

The part of the process in this subsection is shown in figure 8:

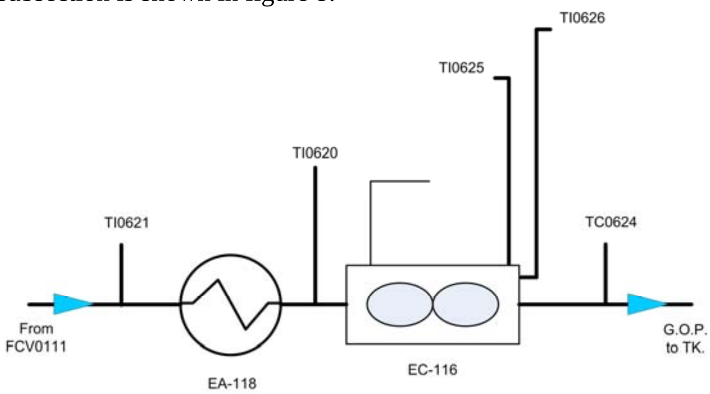


Figure 8. Diagram of Phase 4 of the process

The refined HGO from the stripper enters on the left-hand-side through the servo-controlled valve FCV0111. Initially, the temperature is taken using the Thermopar temperature sensor TI0621, just before the HGO enters the heat exchanger EA-118, the purpose of which is to transfer the heat of the HGO to pre-heat the distillation unit load, and by so doing to make a substantial improvement to the energetic performance of the installation, avoiding the consumption of fuel for heating. An economic saving is achieved in this way and the atmospheric release of pollutants reduced. The temperature of the HGO is taken at the outlet of the heat exchanger by TI0620, and the HGO is cooled in cooling unit EC-116 before storage in a tank at an appropriate temperature without damaging the installation. Sensors TI0625 and TI0626 control the operation of the cooling unit and the outlet to the tank controlled through servo-controlled valve TC0624.

6 Application of the proposal to the process of pumping the refined HGO fraction to storage tanks

The proposed method is now applied to the HGO extraction pipe from a petrol distillation tower. More specifically, it is applied to the subprocess that involves pumping the refined HGO fraction into storage tanks (phase 3 – section 5.3), the schematic diagram for which corresponds to figure 7. The reason for applying it to this part of the process lies basically in the extent to which operators are free to adjust the control given its margin of manoeuvre, so that the other subprocesses that work with fixed parameters under certain conditions do not become unstable. In essence, the level in the stripper (DA-102) is controlled. Table 1 shows the variables that affect the process.

Table 1. Variables that affect the process separated into phases, with their ranges and unitary values.

Variables	Range	Units
Phase 1		
Temperature TI0243	270-350	°C
Phase 2		
Caudal FC0115	0-1800	kg/h
Phase 3		
Level LC0104	0-100	%
Flow FC0111	0-35	m^3/h
Phase 4		
Temperature TI0621	50-350	°C
Temperature TI0620	50-350	°C
Temperature TI0625	50-350	°C
Temperature TI0626	50-350	°C

The distributed control system available at the plant is a Honeywell TDC 3000. User privileges in this system allow the operator to do little more than adjust the control parameters and set values for the process variables. Thus, in order to implement and test the proposal it was necessary to have privileges from the corresponding department, through a limited access module that allows direct access to the network. Thus, the process signals that are read are recorded in *.txt files that will be periodically loaded by the software responsible for implementation, and the signals that are sent to the plant on the basis of the proposal are also written into *.txt files and then loaded by the plant control system at regular intervals. The regulator is a virtual controller that takes signals from the plant through a .txt file, which are fed into the Simulink Matlab software. At a set point signal, the plant receives the required water level and adjusts the proportional valve to regulate the input flow into the stripper.

6.1 A KBS based on operational range

The operating conditions of the system are virtually infinite and certain values must therefore be chosen. Coherent estimates are necessary to achieve good results and it makes no sense to obtain parameters for multiple cases. One approach is to choose a reasonable amount of equidistant values and observe the parametrical changes in each case. An opportunity arises to define new intermediate values if there are substantial changes from one value to another.

Certain characteristics of the stripper will not vary such as its base area or the countercurrent steam pressure. In this case the only significant term that defines the operating conditions or gains adjustment rules of the controller is the level of the tank. Taking the plant into account and the value ranges that might apply to the level of the tank, ten different operating conditions (ranges) were established: (30%-35%), (35%-40%), …, (75%-80%). As it will be seen in the final results, the chosen range of tank filling values will be sufficient to cover the entire operating range of the system.

6.2 Acquiring controller tuning gains for different operating ranges

A hysteresis block could be selected to obtain the regulator parameters of the different working points, in parallel with the PID controller, before applying the Relay Feedback method.

The Relay Feedback method [13] is an alternative to the Ziegler-Nichols closed loop [40-42], for the empirical location of the critical gain (K_c) and the period of sustained oscillation (T_c) of the system. The method, developed by Aström and Hägglud [15, 43], fixed the system in its oscillation state. Its implementation scheme is shown in Figure 9. The Relay Feedback has the advantage that an adjustment can be made to the set point at any time.

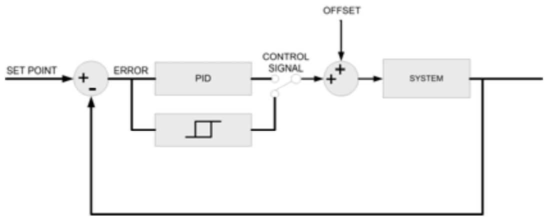


Figure 9. Diagram of Relay-Feedback with relay and PID controller option

This system oscillation has a period with approximately the same value as the period in the Ziegler-Nichols method. A relay with hysteresis centred on the zero value with an amplitude *d* and a hysteresis window width of *h* is recommended for the general method.

6.3 Methodology

Obtaining T_c and K_c parameters. As this particular case study works with a relatively slow system, there is no need to implement the hysteresis cycle mentioned in the above explanation of the Relay Feedback with a window. Instead, a simple comparator is enough (h=0 and d=0.5). The offset, which in this case would be zero, is not necessary. When the system is in operation and sufficient time has elapsed, oscillation is stabilized and periodic. It is then necessary to pay attention to the final zone, and with the expressions for the Relay Feedback method, the extracted parameters are T_c and K_c. It is important to select the parameters in such a way that the values that are attained do not affect the process.

Getting the initial controller parameters. With the parameters obtained in the previous step, it is possible to get the controller parameters to apply direct formulas, thereby achieving the three terms of the regulator: (K, T_i and T_d). In this system, they will have to be obtained from load disturbance criterion, after which the Ziegler-Nichols closed loop method is applied [42].

Parameter fine-tuning. If the results are unsatisfactory, subsequent manual fine-tuning may occasionally be needed after having obtained the parameters with the relay feedback method. This is a delicate adjustment which should not at any point saturate the output controller. A compromise has to be found, without the proportional component (K) being excessive, that would cause a rapid response in the output and little over-oscillation, which would apparently be ideal. However, under these conditions the proportional valve will be in a state of constant flux, which will lead to its deterioration within a short period of time. In conclusion, it is necessary to search for gradual outputs, without saturation or sudden changes.

Obtaining parameters on a case-by-case basis. Taking all the above points into account, the criteria for the fine-tuned controller parameters in each case are minimum overshoot and maximum speed for the restrictions presented in the preceding paragraphs. Accordingly, this leads to the parameters shown in Table 2:

Table 2. Controller parameters obtained for each rule

Level	K	T_i	T_d	Level	K	T_i	T_d
30% - 35%	4.1	25	6.1	55% - 60%	3.0	35	8.0
35% - 40%	3.9	28	6.9	60% - 65%	2.8	38	8.0
40% - 45%	3.8	31	7.3	65% - 70%	2.7	39	8.2
45% - 50%	3.5	32	7.6	70% - 75%	2.2	41	8.4
50% - 55%	3.1	34	7.8	75% - 80%	2.0	40	8.4

Neural Network implementation. A different MLP [28] network was applied for each operation condition range in this research, in order to detect parameter values that lead to system instability. Firstly, it was necessary to obtain the transfer function for each operating point under consideration. To do so, the system identification was obtained at each point by applying an ARX (Auto-Regressive models with eXogenous inputs) method [39] using the Matlab Identification Toolbox. As when the controller parameters were obtained, in this case it is also important that the signal employed in the identification of the plant should not affect the stability of the process. Other identification methods used were AR (AutoRegressive model) and ARMAX (AutoRegressive Moving Average model with eXogenous inputs model) [39] but the best results were achieved with ARX for the plant used in the experiment (table 3 shows the Fit between the real plant and the model, and the final prediction error (FPE) that provides a measure of model quality).

Table 3. Comparison of identification method parameters (Fit and Final Prediction Error)

Transfer function range	AR		ARX		ARMAX	
	Fit(%)	FPE	Fit(%)	FPE	Fit(%)	FPE
30% - 35%	49.2	> 10e-6	73.2	< 10e-6	62.1	< 10e-6
35% - 40%	53.4	> 10e-6	75.1	< 10e-6	65.2	< 10e-6
40% - 45%	53.6	> 10e-6	76.3	< 10e-6	70.9	< 10e-6
45% - 50%	53.1	> 10e-6	76.8	< 10e-6	71.8	< 10e-6
50% - 55%	54.1	> 10e-6	77.5	< 10e-6	72.9	< 10e-6
55% - 60%	54.0	> 10e-6	79.4	< 10e-6	73.2	< 10e-6
60% - 65%	52.2	> 10e-6	79.3	< 10e-6	73.8	< 10e-6
65% - 70%	52.8	> 10e-6	79.5	< 10e-6	73.5	< 10e-6
70% - 75%	52.6	> 10e-6	80.2	< 10e-6	72.8	< 10e-6
75% - 80%	51.9	> 10e-6	79.4	< 10e-6	73.1	< 10e-6

Stability structures were then obtained, and the ANN architecture was trained with those same points. An ANN was obtained for all operating points. The number of neurons in its intermediate layer fluctuated between 6 and 8. The structure was adopted after rigorous testing with different numbers of neurons in the hidden layer (tests were conducted with 4 to 9 neurons in the intermediate layer) for every neural network.

The activation transfer functions of the hidden layer are hyperbolic tangent types. Other activation functions were probed, although the best results for each operation point in all the ANNs were achieved with the hyperbolic tangent function (table 4). In the output layer, a hard limit transfer function was applied to indicate whether the parameters programmed by human operator are valid or whether it is necessary to apply corresponding stored parameters to the operation point.

Table 4. Comparison between ANN activation transfer functions (Linear transfer function, Log-Sigmoid transfer function, Tan-Sigmoid transfer function) in hidden layer (best error and number of neurons in middle layer)

ANN range	linear		logsig		tansig	
	Error(%)	No Neur.	Error(%)	No Neur.	Error(%)	No Neur.
30% - 35%	19	8	12	7	2	7
35% - 40%	21	9	14	6	2	6
40% - 45%	23	8	14	6	1	7
45% - 50%	25	7	16	8	0	8
50% - 55%	23	8	13	8	0	8
55% - 60%	20	9	13	7	2	7
60% - 65%	24	9	12	7	1	7
65% - 70%	27	7	14	8	0	7
70% - 75%	30	8	15	8	0	7
75% - 80%	31	8	14	7	0	8

Once this configuration had been selected, the different characteristics of the training carried out with back-propagation learning were set. The training steps were fixed at ranges of 400 to 700 epochs, with an average error of below 1% at the end of the training. The MLPs were trained off-line, although their performance was verified on line.

7 Method assembly and results verification

The method was run in the Matlab/Simulink environment. A National Instruments data acquisition card (model USB-6008 12-bit 10 KS /s Multifunction I/O) was chosen for operations at the laboratory plant, but for the field tests it was necessary to interact with the manufacturer's control software. Bearing in mind that the implementation and development platform for the method was Matlab/Simulink, the process inputs developed in Simulink had to be implemented in blocks 'Level – 2 M – file, S-Function' to ensure that a .txt file would be periodically consulted and also periodically updated by the existing control software in the process with the relevant variable. In much the same way, the control signal provided by the implemented controller is programmed with a block of the same type in another .txt file, which is accessed by the manufacturer's software to read the value and control the actuator. The diagram of the process is implemented in Simulink (Figure 10).

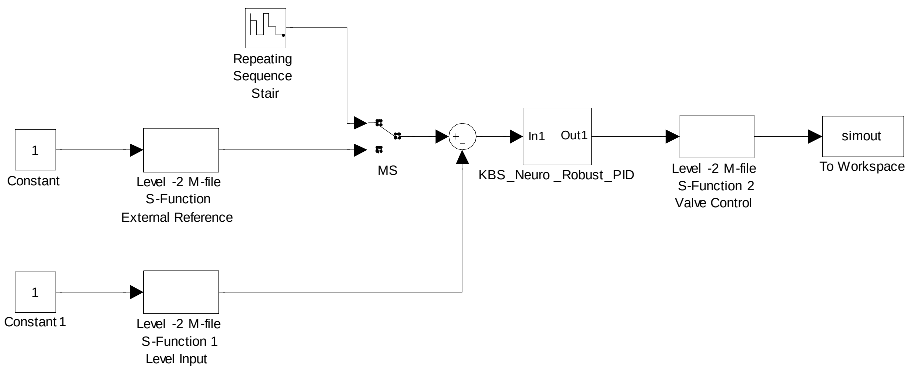


Figure 10. System implemented in Simulink

There are two ways of fixing the set point for the laboratory tests on the plant: the first is to generate a sequence of repeating values; the second is to set its value using other .txt file. One of the two options has to be chosen.

The next step is to develop the previously described controller; creating the output diagram blocks in Simulink (figure 11).

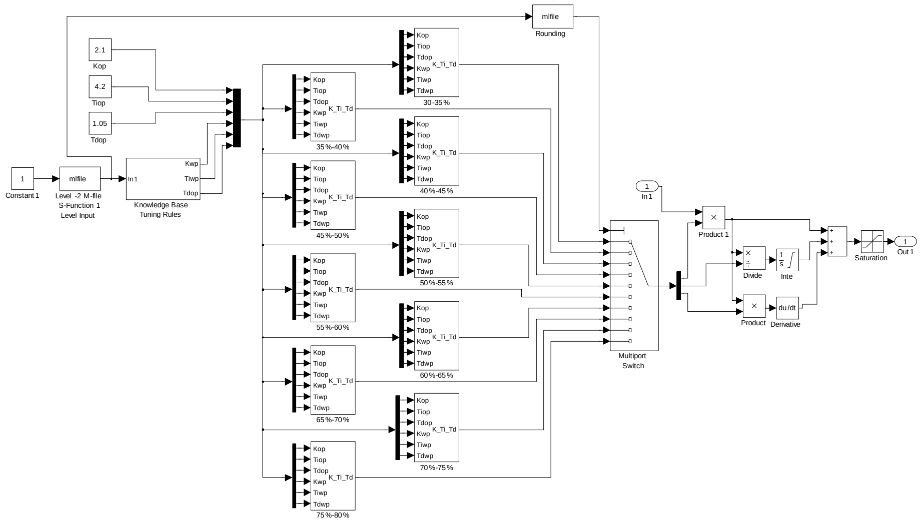


Figure 11. Implementation of the controller

Figure 11 shows the implementation of a PID controller, the parameters for which are the outputs of the multiport switch. Its inputs depend on the tank level and the parameters that are manually programmed by the operator. There are 10 blocks (Range Blocks) in the above diagram (Fig. 11), one for each range level (i.e. 40% to 45%). Their internal layout is shown in figure 12, where additionally, inside each Range Block there is a further block (subsystem2) that contains the scheme on the right, which is the topology of figure 2 implemented in Simulink (Matlab).

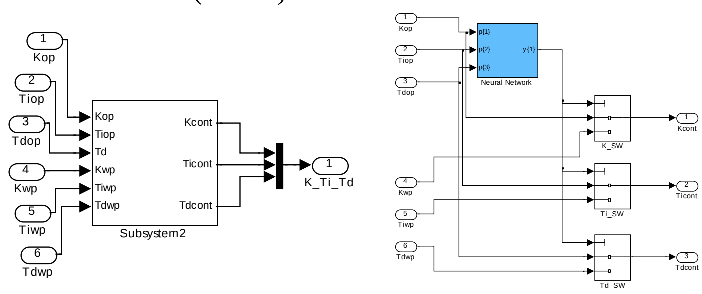
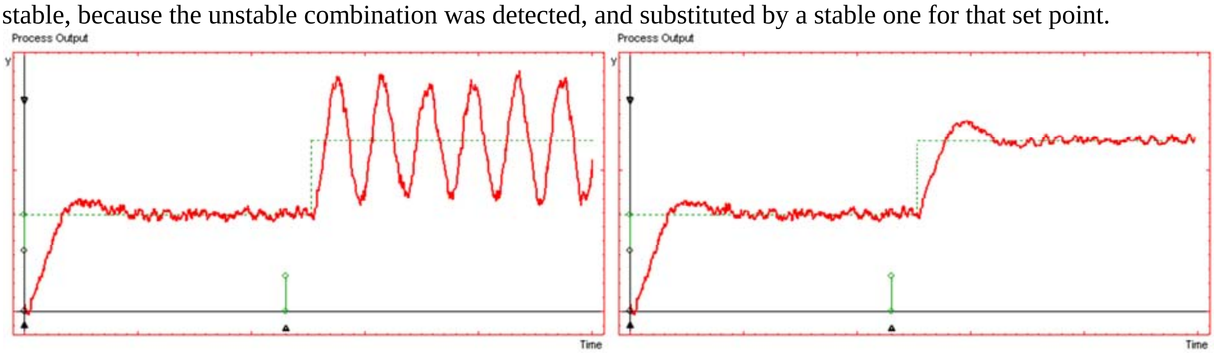


Figure 12. Range Block internal scheme and Subsystem2 block contents.

The pins In_1 and Out_1 (Fig 11) are the KBS_Neuro_Robust_PID block pins in figure 9, which send a control signal to another .txt file, to take direct action on the proportional valve (FCV0111).

In this way, the Controller will select the most appropriate parameters for the work point which it is running. When an operator modifies the parameters, they are evaluated by the system and if there is a risk of system instability, the parameter are automatically replaced by other more appropriate ones for the operation of the work point, in such a way that they guarantee system stability.

A graph is shown in figure 13, as an example of the way the system functions. It starts off at 35% and has fill limit of 55%, until it reaches a stationary level over time. Subsequently, the controller parameters are changed by the operator at the point in time marked mid-way along the X axis by a small triangle. The combination of programmed parameters is an unstable combination for the set values which proceed to fill the tank with liquid to a level of 70% as may be seen in graph 13a. However, as may be seen in graph 13b, which corresponds to the proposed method, after programming the new set values, the system remains stable, because the unstable combination was detected, and substituted by a stable one for that set point.



a) **b)**

Figure 13. Experimental operational test on the tank level control system

8 Conclusions

A new method for a bio-inspired control system is presented in this study for a real refinery plant process. It retains the advantages offered by the conventional PID system on which it is based, as well as the possibility of applying it to non-linear systems while maintaining invariable specifications throughout the operational range. Moreover, it is set up to ensure that manual modifications to the controller parameters made by an operator to input particular specifications, for whatever reason, will at no time lead to control system instability.

The novel proposal in this research is an option to take into account in non-linear systems that function throughout the range of operation, and that can be divided into zones with linear behaviour in which the control of the PID regulator is feasible. It is therefore an alternative to different types of self-adjusting controllers. It should be stressed that the solution is not easy to implement but the work involved is greatly simplified with today's programmable controllers and the computing tools found in modern refineries.

Multiple tests of the proposed bio-inspired method on the refinery plant which involved tests on the different work points yielded satisfactory results. The system is robust when an operator introduces dangerous parameter combinations in order to change operating specifications. The system component prevents system instability and restores the programmed safety combination for the relevant operation point. It has to be said that the technique functioned very satisfactorily, considering the size of the tank which fills up and empties very rapidly. The temporal specifications are also very similar at all points of operation after different changes made to the level of the liquid, a very important fact in the case of operation with no modifications made to the parameters.

The great advantage that this technique introduces is to be highlighted in the context of refineries from the standpoint of improvements, given that it is a field that is quite closed to possible modifications. Moreover, with regard to the plant operator, the absence of training needs after the proposal is introduced is worth mentioning; the operator continues to perform the same tasks; with equal ease given the robustness of the proposal.

It is also important to highlight that in the refinery, for which distributed control is in many cases available, the proposal is ideal. This is because this technique can be applied to the different control loops that exist, without being concerned that it will negatively affect other control loops in the plant. Even, if earlier and subsequent processes are taken into account, the consequence of its application can be beneficial for the entire plant setup.

Future work along the same lines responds to a series of challenges. The first proposal is to apply the new method to other real process based on PID controller. Possible case studies would be the control loops used in electricity generating stations or manufacturing process. It is often the case that the advanced control centres in these sectors leave experienced operators with a certain degree of control to vary control parameters and in consequence specifications. Other future work will apply the method to make a system more robust not only against possible instability, but also against undesired specifications. Work will therefore continue on introducing greater stability into structures so that they function within the range of values for a given specification.

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