

Human Operator Based Fuzzy Intuitive Controllers Tuned with Genetic Algorithms

Filipe Leandro de F. Barbosa*, Ming Tham**, Jie Zhang**, André Domingues Quelhas*

**Petrobras SA – Petróleo Brasileiro SA – Rio de Janeiro – RJ, Brazil*

*Rua Visconde de Duprat s/n – 8o andar, CEP: 20211-230 – Rio de Janeiro – RJ, Brazil
(Tel: +55 21 3487-3474; e-mail: filipeleandro@petrobras.com.br, quelhas@petrobras.com.br)*

*** School of Chemical Engineering and Advanced Materials, Newcastle University,
Newcastle upon Tyne NE1 7RU, UK (e-mail: ming.tham@ncl.ac.uk, jie.zhang@newcastle.ac.uk)*

Abstract: A recent study (Desborough and Miller, 2001) revealed that a great majority of the control loops that operate in industry use the PID (Proportional-Integral-Derivative) controllers. Furthermore, the study has shown that more than one third of these loops were switched to manual for a considerable period of time, indicating poor behaviour of the controllers' performance. As was also reported, the gap between the industrial practice and the process control theory remains unchanged over the years, indicating that industry is looking for simple and easy to use technologies. The present research offers an alternative control scheme that intends to be a step towards introducing a new technology for practical implementation in industry. The controller is developed aiming to emulate human operators' actions when manually controlling SISO systems, subject to disturbances. The developed control scheme is based on an intuitive hypothetical model that describes the way human operators (HO) act in a manual control loop, generating the Human Operator Based Intuitive Controller (HOBIC). Since human operators typically use vague terms when describing control actions, it is natural to use fuzzy logic to express manual control actions. The HOBIC is then extended using the Fuzzy Logic theory. Membership functions within Fuzzy-HOBIC are tuned using a genetic algorithm (GA). The tuning does not require a process model. It is based on historical process operation data containing manual operation actions from experienced operators. The traditional GA is modified to cope with real valued optimisation variables and their constraints. Results show that the hypothetical model created for the HO's actions is appropriate, since the generated control actions by the HOBIC and Fuzzy-HOBIC can approximate those of human operators. The control signal generated has the same discontinuous nature of the HO's one.

Keywords: advanced control strategy, human operator model, auto-tuning, fuzzy logic, genetic algorithm

1. INTRODUCTION

Process Control theory has been well explored over decades to, at first, automate the manual control loops and thereafter, to maintain and improve them. However, it is observed that there is a gap between the Industry and the state of the art theory (Desborough and Miller, 2001). Industry presents, very often, a high resistance to put into practice what was recently developed. As a result, the vast majority of the control loops observed operates using traditional PID (Proportional-Integral-Derivative) controllers. Such kinds of controllers are very simple to apply and understand, when compared to other more advanced approaches.

However, recent studies have revealed that a great part of those PID control loops are having a poor behaviour or are operating in manual. As an example, Desborough and Miller (2001) published a survey showing that 97% of the regulatory controllers from over 11,000 control loops of refining, chemicals, pulp and paper industries use the PID strategy. Furthermore, this work mentions that only one third of these controllers provide an acceptable performance. It is

also commented that this fact is in accordance with the work of Bialkoski (1993).

This leads to the challenge of investigating those control loops to verify if they can be improved by simply reviewing the applied PID strategies or, in some cases, by studying the applicability of new techniques. Nevertheless, being aware of Industry's inertia to new developments, the challenge is even greater: to develop a control strategy with a great practical appeal, so it can be easy to understand and apply.

In the authors' experience, very often, newly developed control strategies are difficult to understand by the operators, the end users of the controllers. Hence, at the first indication of bad behaviour of the loop, the operators simply switch the controller to manual and if the process engineer does not verify what caused the problem, the operator normally will not turn it into automatic again. This will reinforce the statistics of loops in manual in Industry and quickly put the new technology into disrepute.

The review by Desborough and Miller (2001) also explicitly shows that 36% of the analysed PID loops are operating in manual for at least 30% of the observed data (5,000 samples

at the dominant system time constant). Hence, almost 4,000 controllers have been switched to manual for a considerable amount of time.

This work has the objective of developing a technique which is easily understandable by the operators. By doing so, the end users of the control loop will tend to support the idea and maintain the controller in automatic.

One way of getting support of the operators is to make the control loop behave as if the loop is in manual. In other words, the controller has to give actions to the final control element in the same way as the operator would do, if he was controlling the loop. If the new controller manages to mimic this behaviour, it is less likely that the operator will switch the controller to manual.

Nevertheless, trying to emulate the operator's actions in a control scheme is not something new. Until 1966, over 200 works related to this subject were published, according to Costello and Higgins (1966).

The great majority of the research on Human Operator (HO) modelling in the past was for application in mechanical systems, such as aircrafts and vehicles dynamics (Kleinman, Baron and Levison, 1970). Investigating more recent papers in this field, it can be noticed that this area of modelling the human behaviour for applications in control systems still attracts the researchers' attention as can be seen by the works of Enab (1995); Zapata, Galvão and Yoneyama (1999); Ertugrul and Hizal (2005). However, there is still a lack of real applications of such control technique in the Process Control field.

The present research aims to construct a control system with direct application in the continuous Process Control Industry, also by modelling Human Operator actions. However, it is different from the vast majority of the previous works in this modelling field. Due to the fact that the system dominant time-constants in the Process Control area are, in general, greater than in the mechanical systems, the concern about the HO's reaction time becomes negligible. Hence, the HO modelling techniques applied by Kleinman, Baron and Levison (1970a, b) are not suitable for sluggish Process Control applications. In the same manner, Zapata, Galvão and Yoneyama (1999) presented a mechanical application where the system time-constant had the same order of magnitude of the HO responses. As a result, an ARMA (autoregressive with moving average) model for the HO had to be identified to smooth the operator actions, considered to be noisy and less consistent than the ARMA model ones.

Another important issue to be discussed is the implementation strategy that the recent works used to model the HO control actions. They applied a model-free type technique. In other words, the model was extracted based upon input-output data, either by using Neural Networks approach (Enab, 1995), Neuro-Fuzzy techniques (Ertugrul and Hizal, 2005) or simply by extracting Fuzzy rules directly (Zapata, Galvão and T. Yoneyama, 1999).

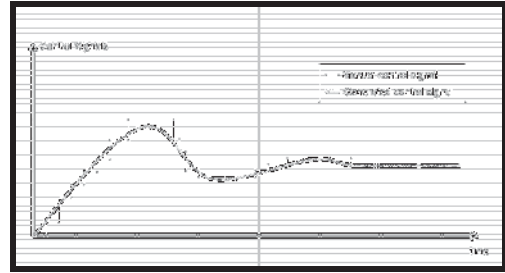


Fig. 1: Fictitious representation of a Manual control signal and a generated control signal using a model-free approach.

Although the model-free approach is able to approximate the HO behaviour, as the results of these works show, it fails to present a clear and easily understandable description of how the HO behaves and which rule system it uses to generate the actions. Even when applying Fuzzy Logic (FL) technique directly, as done by the work of Zapata, Galvão and T. Yoneyama (1999), the model-free approach generated a set of 15625 rules, which is quite difficult to understand and maintain in a practical application.

In the present work, a model-based approach is applied using the FL theory. Hence, the number of generated Fuzzy rules is expected to be much less than when using the model-free approach, and therefore easier to understand and apply in the Process Industry.

The work developed by Enab (1995) is of particular interest because it was related specifically to Process Control. The application presented was the control of the level in a tank, which has a nonlinear behaviour. This paper shows that the manual operation can be approximated using a Neural Networks approach. However, the generated control signal is continuous, compared with a "stair-like" manual signal, as can be seen by Fig.1. The difference in the signal's nature is clear. On the other hand, a FL model-based approach would be able to produce a "stair-like" signal, if the proposed rules that comprise the Human Operator model are designed to perform this task. Nevertheless, one disadvantage of the FL model-based system is that the resultant Fuzzy Logic Controller (FLC) will need to have its parameters adjusted so it will be able to reflect the behaviour of a given operator. Thus, these Membership Functions (MFs) have to be appropriately adjusted so that the generated control signal approximates the HO behaviour.

One way to cope with this disadvantage of the model-based FL approach is to come up with an automatic procedure for finding the appropriate adjustments of the MFs. In this work, this procedure is called "tuning". As there are many possible combinations for the MFs parameters, the search space for the tuning procedure is inevitably large. To solve such kind of high dimensional search space problems, Genetic Algorithms can be applied (Orvosh and Davis, 1994). In this work, a Genetic Algorithm (GA) is developed to tune and validate the proposed FL model.

The remainder of this work is organised as follows. Section 2 gives a general idea of the desired behaviour of the developed controller based on a hypothetical model for the way the HO acts in a manual control loop. In Section 3, the controller is

formally presented and its natural extension, via FL approach is achieved. In Section 4, a Genetic Algorithm (GA) is used to select the appropriate FLC parameters. A nonlinear Process Control application is tested with the developed FLC to compare the generated control actions with the manual operation in Section 5, where the results of the system simulation and discussion are presented. Section 6 summarises the conclusions of this paper and recommendations for future work.

2. HUMAN OPERATOR BASED INTUITIVE CONTROLLER DEVELOPMENT

2.1 Human Operator tasks and responsibilities

In a process plant, commonly, the HO has the responsibility of maintaining the plant under control, mainly by manipulating the final control elements, in manual loops, or by changing the controllers' set-point (SP) values.

The first concern of the operators is about safety. Right after the security concern is the production task. The production throughput should not decrease in time. Supervisors are always checking for production problems and possible causes of such incidents.

2.2 Human Operator's behaviour model

Two modes of operation may be defined for the HO:

- A. When changing the operating conditions (SP-Tracking);
- B. When rejecting disturbances (Disturbance Rejection).

In the first mode of operation (Mode A), the operator, to not disturb the system, will change the operating conditions only when necessary by slow changes in the final control element. This tends to minimise some problems such as interactions between loops, for example. This manual procedure is equivalent to changing the controller SP, when it is in automatic. Hence, Mode A is called SP-Tracking mode of operation. In Mode B, to reject a given disturbance, the behaviour of the operator is normally more aggressive. This is natural, since his task is to maintain the process plant under control.

An intuitive algorithm to describe the way the operator adjusts the final control element (Control Valve, for example), considering a single input single output system, subject to disturbances, can be described as follows:

1) Is the PV following the desired path (SP)?

If 'Yes' then "Do nothing. The process is under control"

Else

If Mode A: - apply Mode A procedure;

If Mode B: - apply Mode B procedure;

End

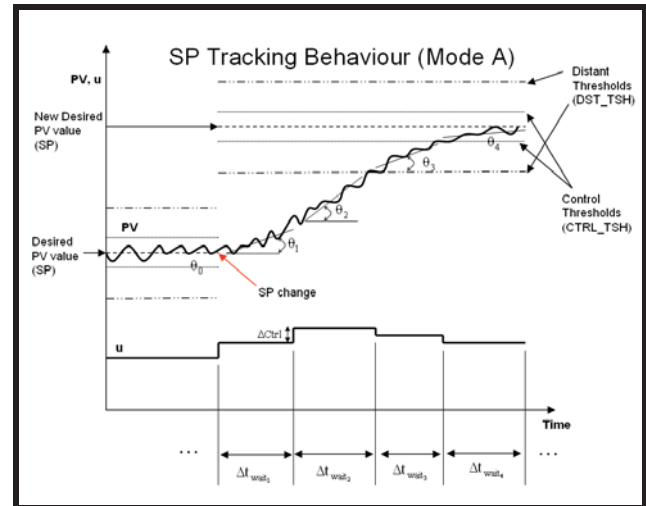


Fig.2: Intuitive HO behaviour when in Mode A of operation.

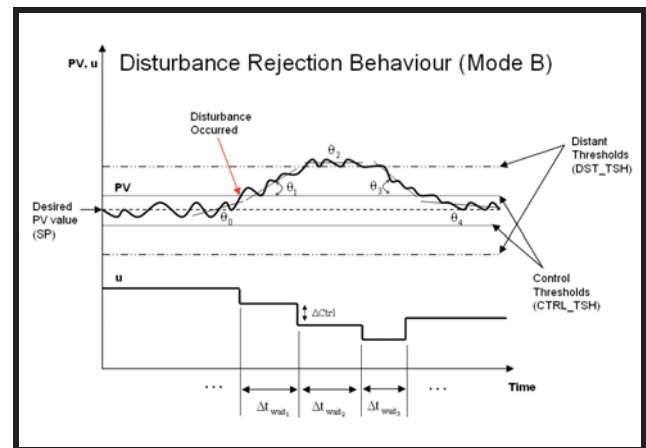


Fig. 3: Intuitive HO behaviour when in Mode B of operation.

2) When in Mode A:

Manipulate the Control Valve appropriately and wait for the system to react. If the trend of the PV is already going to the desired SP with an appropriate "velocity" do not change the Control Valve value. However, if the PV trend is going too "fast" or too "slow" to the desired SP, change the Control Valve appropriately and wait for the system's response

3) When in Mode B:

Perform the same actions done in Mode A, but with more aggressiveness, that depends upon the value of the PV.

From Fig. 2 and Fig. 3, some subjective terms mentioned in items 1, 2 and 3 such as "velocity", "slow" and "fast", are clarified. It can be observed that as the operator inspects the PV, he determines if the PV is under control by observing three variables, mainly:

- Variable 1 – Angle that the PV trend makes with respect to the desired SP;
- Variable 2 – Distance between the PV and SP;
- Variable 3 – Is the error increasing or decreasing?

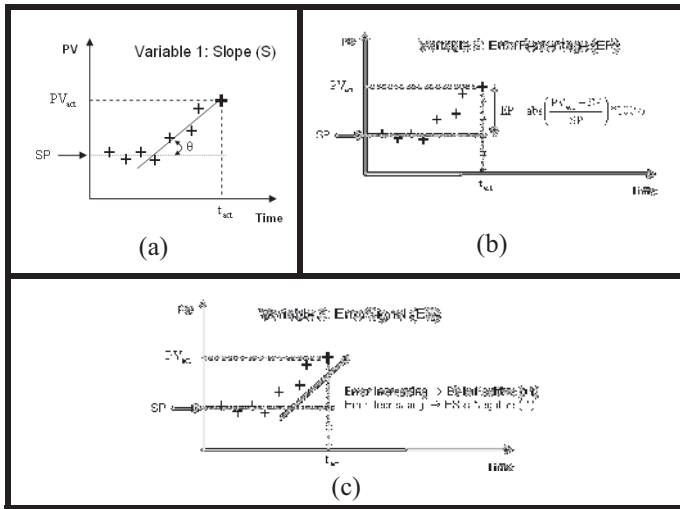


Fig.4: Variables used to encapsulate the HO's behaviour in the HOBIC.

Hence, the action taken in the Control Valve will be generated after analysing these three variables. After the action, the operator has to wait some time until the system reacts to it. The minimum time to wait (Δt_{wait}) should be greater than the Process time-delay. Thus, after observing the result of his action, the HO judges again the variables 1, 2 and 3 and takes another action or waits, if the PV is already under control again or if the PV trend is behaving as intended.

The PV is considered to be “behaving as intended” if it is approaching the SP within a given range of angles (“velocity”) at a given distance from the SP that the operator establishes in his mind for that specific system. Therefore, if the angle is not within the desired range of values for a specific distance away from SP, then the control action is increased or reduced appropriately. From Fig.2 and Fig.3 it is clear that for SP-tracking (Mode A) the actions are less aggressive than when rejecting disturbances (Mode B). These figures also show that the HO has in his mind imaginary thresholds to determine how far from the SP the PV is (CTRL_TSH and DST_TSH).

2.3 The HOBIC and its natural extension –Fuzzy-HOBIC

Fig. 4 suggests the way variables 1, 2 and 3 are obtained. Variable 3, denoted as ErrorSignal (ES), reflects whether the error between SP and PV is increasing (“+1”) or decreasing (“-1”). Variable 2, shown in Fig. 4(b), defines the absolute value of the error percentage between PV_{act} and SP, i.e. ErrorPercentage (EP). The reason for defining the distance between PV and SP as an error percentage measure is because the operator tends to analyse the PV value relatively to its desired value to judge if the PV is close or far from the SP. For example, for SP values of 100 units, deviations of 3 units can be considered to be “small” (3%) by the operator, and no action would be taken. However, if the SP is zero, the EP will be, by definition, the absolute value of the PV times 100%. Variable 1 defines the angle, in degrees, that the PV trend makes with the SP, denoted by Slope (S) in Fig.4(a).

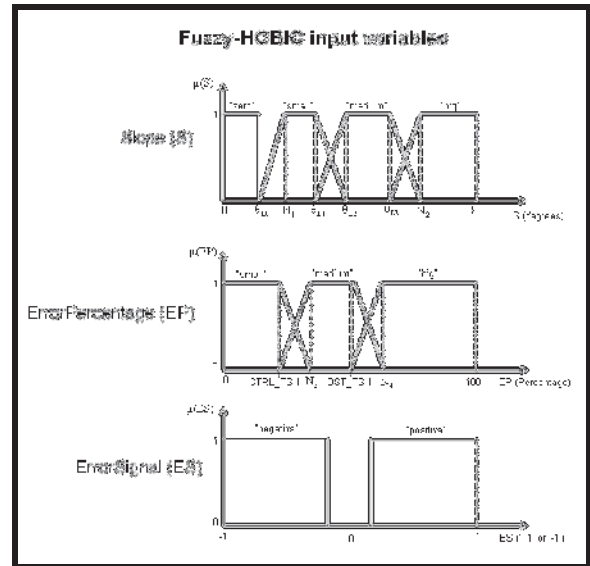


Fig. 5: Fuzzy-HOBIC Linguistic variables.

The Slope can be obtained numerically using Multi-variable Least Squares (LS). From Fig. 4(a), one can notice that the angle is obtained by using five samples (PV_{act} and the past four samples). This is a good compromise between being less sensitive to the presence of noise and getting the actual PV trend. It is being assumed here that the sampling period used is sufficiently low to capture the system dynamics (eg.: 10% of the dominant time-constant) and sufficiently high to not to capture only the noise dynamics.

After defining how the variables 1, 2 and 3 are determined in the HOBIC, the next step is to specify the thresholds CTRL_TSH and DST_TSH. The Control Threshold is, by definition, the limits within which the operator judges that the system is under control and no action is taken, when the PV has “small” Slope values. The Distant Threshold is obtained by determining the distance between PV and SP, when the operator’s actions start to increase significantly. These limits are also automatically detected (Section 3).

2.4 Determining the HOBIC's rules

To be able to embed in the HOBIC the rules that the operator is using, four angle limits are defined: $\theta_{L0}, \theta_{L1}, \theta_{L2}, \theta_{L3}$. The first angle limit (θ_{L0}) is a dead band limit. In other words, the HOBIC will consider that the Slope is zero if S is less than θ_{L0} . The other three limits are distributed from θ_{L0} to 90 degrees, dividing this region into intervals. For each region of Slope values and considering the EP and ES variables, a specific action is taken in the Control Valve. Judgment about what action is to be taken given the system state (S, EP, ES) is performed by a set of 20 rules. However, these rules can be simplified by applying the FL approach.

The actual HOBIC variables S, EP and ES are considered to be linguistic input variables. The Linguistic values for these variables are as follows:

Table 1: Fuzzy-HOBIC rules definition.

Rule N ^o	Rule Definition	Abs (deltaAction)
1	IF (S is zero) and (EP is small)	zero
2	IF (S is zero) and (EP is medium)	small
3	IF (S is zero) and (EP is big)	medium
4	IF (S is small) and (EP is small)	small
5	IF (S is small) and (EP is medium)	small
6	IF (S is small) and (EP is big)	medium
7	IF (S is medium) and (EP is small)	small
8	IF (S is medium) and (EP is medium) and (ES is negative)	Zero
9	IF (S is medium) and (EP is medium) and (ES is positive)	medium
10	IF (S is medium) and (EP is big) and (ES is negative)	zero
11	IF (S is medium) and (EP is big) and (ES is positive)	big
12	IF (S is big) and (EP is small)	medium
13	IF (S is big) and (EP is medium)	medium
14	IF (S is big) and (EP is big) and (ES is negative)	small
15	IF (S is big) and (EP is big) and (ES is positive)	max

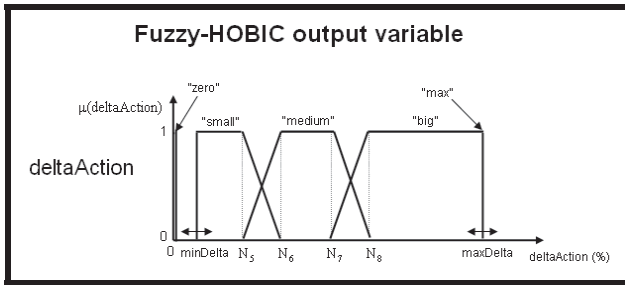


Fig. 6: Fuzzy-HOBIC output variable description.

- Slope (S): “zero”, “small”, “medium”, “big”
- ErrorPercentage (EP): “small”, “medium”, “big”
- ErrorSignal (ES): “positive”, “negative”

The Fuzzy-HOBIC input variables are described in Fig. 5. Each linguistic value is mathematically defined as a MF. Applying FL approach, the rules number is reduced to 15. They are shown in Table 1. This happens without loss of generality because of the advantage that the fuzzy rules give of activating more than one rule at a time.

It is important to notice that the control action is shown in Table 1 as an absolute value. The sign of deltaAction, is determined by observing the ES value. The Fuzzy-HOBIC output variable (deltaAction) is shown in Fig.6. About Fig. 6, the linguistic values “zero” and “max” are applied to force the Defuzzification process to give the numeric outputs zero and maxDelta, according to its respective fuzzy rules.

The process time-delay, minDelta and maxDelta values are assumed to be known inputs that depend upon the application and the HO’s behaviour, as well as the times involved to wait for the system to react, after the control actions are given. To cope with the disadvantage of having many parameters to tune for this controller, an automatic method of tuning the developed Fuzzy-HOBIC using a Genetic Algorithm (GA) is developed.

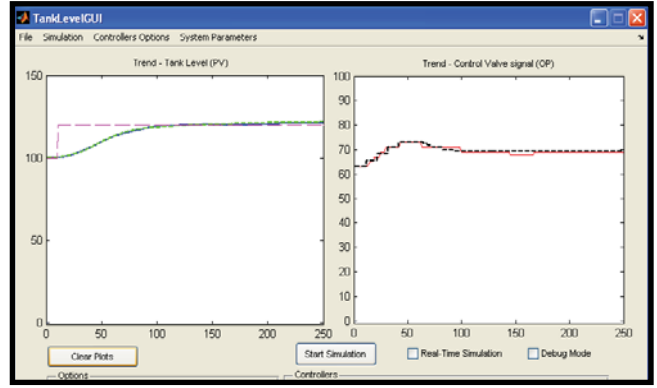


Fig. 7: Fuzzy-HOBIC (dashed lines) vs. Manual Operation (solid lines). Step up test (+20%).

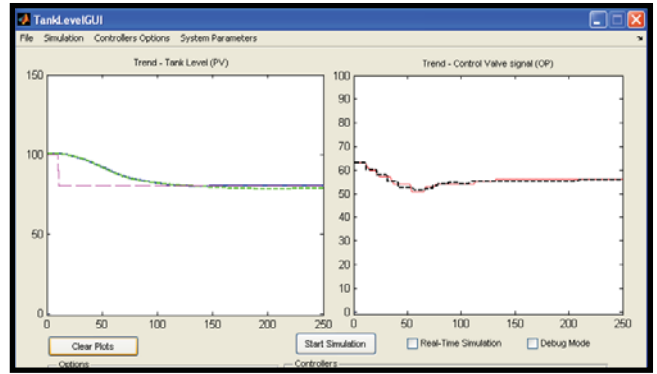


Fig. 8: Fuzzy-HOBIC (dashed lines) vs. Manual Operation (solid lines). Step down test (-20%).

3. APPLYING A GENETIC ALGORITHM TO TUNE THE FUZZY-HOBIC

The objective of the GA is to find values of the 14 parameters (P1-P14) that will make the Fuzzy-HOBIC approximate a given HO’s behaviour. The closer the Fuzzy-HOBIC’s actions are to the HO’s ones the better is the tuning. A suitable objective function, is given by (1), where $U_{man}(i)$ and $U_{FHOIC}(i)$ represent the sample ‘i’ of the manual and the Fuzzy-HOBIC actions from a total of N available samples, respectively.

$$J = \sum_{i=1}^N \frac{(U_{man}(i) - U_{FHOIC}(i))^2}{N} \quad (1)$$

For the developed GA, an elitist strategy is used (Chipperfield, Fleming, Pohlheim and Fonseca, 1994). The initial population is split into two sets which are used to compose three sub-populations. The first set is composed of the best individuals of the population (smallest J values). This set composes the first and the second sub-populations. The first one has a low mutation rate, while in the second a high mutation rate is applied. The low mutation rate in the first sub-population is used to search for local minimums, while the high mutation rates for the second population is applied to find new regions of minimums, trying to avoid getting trapped in local minimums.

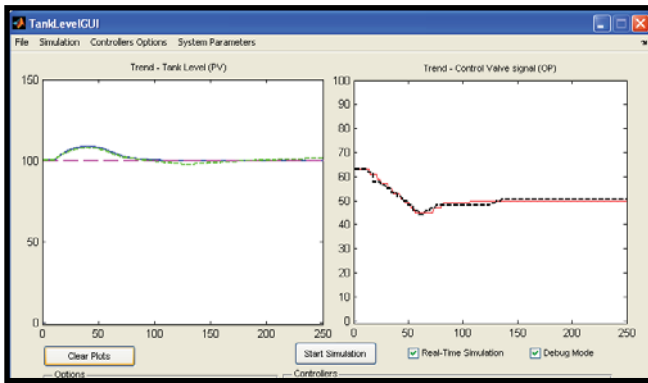


Fig. 9: Fuzzy-HOBIC (dashed lines) vs. Manual Operation (solid lines). Disturbance Rejection up test (+20%).

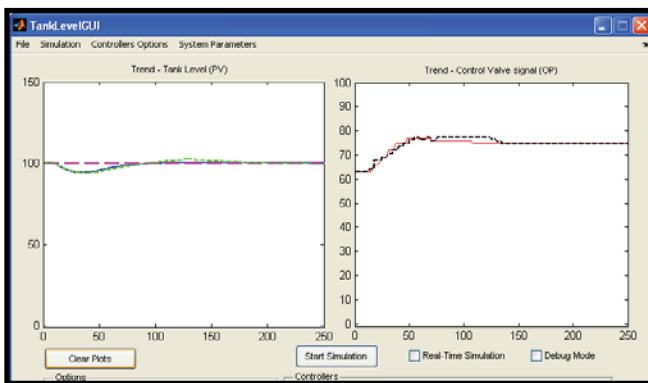


Fig. 10: Fuzzy-HOBIC (dashed lines) vs. Manual Operation (solid lines). Disturbance Rejection down test (-20%).

A third sub-population is composed of the second set of the population. In this case, a high mutation is applied, because of the same reasoning used for the second population.

The convergence criteria applied in this work is either when the best individual from the population does not change for more than 10 generations or when the maximum number of generations is exceeded.

4. RESULTS AND DISCUSSION

The application chosen for testing the Fuzzy-HOBIC is controlling the level of liquid in a Tank, in the same manner as performed by Enab (2005). This is a very common nonlinear application in the process industry. For this specific application, it is also supposed that the level needs a tight control. The input flow control valve is used to regulate the tank level, while the output flow control valve generates the non-measured disturbance. After defining the application to test the Fuzzy-HOBIC it is necessary to develop a simulation environment that reflects the proposed system to be controlled. A Graphical User Interface (GUI) was implemented to simulate the tank level system.

Figures 7-10 show the results obtained when tuning the Fuzzy-HOBIC using the GA approach. It is important to notice, however, that two different tunings were used here: one for sp-tracking and the other for disturbance rejection. The manual operations were generated using the developed GUI, by an operator that got experienced by using the

system. When controlling the level in manual, two objectives were followed: 1) Do not produce any overshoot, when tracking set-point; 2) Try to eliminate the disturbance as fast as possible without making large changes in the control valve. These objectives are in accordance with the HO's behaviour, described in sub-section 2.2. As can be seen by the results, the operator's behaviour could be well approximated the tuned Fuzzy-HOBICs, showing its "stair-like" signals nature.

5. CONCLUSIONS

The results of applying the Fuzzy-HOBIC in a process control simulation have indicated that:

- The rules used to describe the HO's behaviour were adequate for approximating his manual operations in the application tested;
- A process model is not needed to tune the Fuzzy-HOBIC.

As recommendations for future work, it is suggested to test the developed controller in a real Process Control Application. Another possible application of Fuzzy-HOBIC would be to train apprentice operators, as already suggested by Zapata, Galvão, and Yoneyama (1999).

REFERENCES

- Bialkowski, W. L. (1993). Dream versus Reality: a view from both sides of the gap, *Pulp and Paper Canada*, 94 (11), pp. 19-27.
- Costello, R. G. and Higgins, T. J. (1966). An Inclusive Classified bibliography pertaining to modelling the human operator as an element in an automatic control system. *VII IEEE Symp. On Human Factors in Electronics*, Minneapolis, Minn.
- Chipperfield, A., Fleming, P., Pohlheim, H. and Fonseca, C. (1994). *Genetic Algorithm Toolbox: For use with MATLAB - Software and User's Guide*. Department of Automatic Control and Systems Engineering, University of Sheffield, UK.
- Desborough, L. and Miller, R. (2001). *Increasing Customer Value of Industrial Performance Monitoring – Honeywell's Experience*. Honeywell Hi-Spec Solutions.
- Enab, Y. M. (1995). Controller Design for an unknown process, Using simulation of a Human Operator, *Engineering Appl. of Artificial Intelligence* 8(3), pp. 299-308.
- Ertugrul, S. E. and Hizal, N. A. (2005). Neuro-Fuzzy controller design via modelling human operator actions. *Journal of Intelligent & Fuzzy Systems* 16, 133-140, IOS Press.
- Kleinman, D. L., Baron, S. and Levison, W. H. (1970). An Optimal Control Model of Human Response – Part I: Theory and Validation. *Automatica*, vol. 6, pp. 357-369.
- Orvosh, D. and Davis, L. (1994). Using a Genetic Algorithm to Optimize Problems with Feasibility Constraints. *IEEE Conference on Evolutionary Computation - Proceedings (2/-)*, pp. 548-553.
- Zapata, G. O. A., Galvão, R. K. H. and Yoneyama, T. (1999). Extracting Fuzzy Control Rules from Experimental Human Operator data. *IEEE Trans. On Systems, Man and Cybernetics-PartB: Cybernetics* 29(3), pp. 398-406.