



Data-Driven Neuroendocrine Ultra short Feedback Control System for Conical Tank Process

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Abstract: The proportional integral derivative (PID) Controllers are frequently used in industries for nearly a century due to its efficiency, simplicity and flexibility. In recent times, the control of non-linear processes in the industries have turned the attention towards the intelligent controllers such as, Fuzzy Logic Controller, Neural Networks Controller, Adaptive Controller, Genetic Algorithm tuned Controllers, etc. This paper focuses on the analysis of data-driven neuroendocrine ultrashort feedback controller (DNUC) for conical tank level process. A conical tank is a highly nonlinear process due to the variation in the area of cross section of the level system with change in shape. In this work, data-driven biointelligent controller is designed for the control of nonlinear process to guarantee the exact level maintenance. For this work, DNUC is compared with Conventional P, PI, PID and Fuzzy Logic Controller. The simulation results are obtained for the nonlinear conical tank process. Simulation results show that DNUC has a better performance compared to other controllers.

Keywords: Data-driven control, ultrashort feedback unit, neuroendocrine ultrashort feedback, Virtual reference feedback tuning, conical tank.

I. INTRODUCTION

In industries various types of control problems arises depending on the type of the process that the industry is meant for. As the nonlinearity in the process variables increases the formulation of control action becomes more challenging. Nonlinear conical tanks are inevitable in food processing industries, waste water treatment plant and hydro-metallurgical industries. Since there is nonlinearity and ruthless change in cross section, the control of conical tank is a difficult problem. From the time immemorial industries use conventional controllers for the controlling of variety of processes. Among the available conventional controllers, control engineers prefer to use PID (Proportional Integral Derivative) controller due to their performance. Since PID controllers are employed in most of the industries, it is sometimes referred to as work-horse of process industries. Even though the PID has its own merits, it fails to give fast response as the process linearity increases. This fact makes the PID controller not suitable for level controlling task of conical tank. To overcome this drawback, nonconventional controllers such as Fuzzy Logic Controller, neural network controllers, Genetic Algorithm tuned Controllers, etc. are introduced. These controllers are based on some biological processes or it can be otherwise treated as mathematical formulations of various biological processes in nature.

The biological systems generally the human body are the motive in designing intelligent controllers. Among different types of biological systems, the regulation

principles of the subsystems in human body are taken as enrichment for improving the conventional controllers [2]–[4]. Liu et al. [2] proposed a neuroendocrine ultrashort feedback controller (NUC). It is a nonlinear algorithm that provides a compensation for a conventional controller using conventional controller's output and the system's error feedback. Ding and Liu [3] introduced an intelligent bicooperative decoupling controller based on the modulation mechanism of internal environment in body. Inspired by the regulating principle of the endocrine system a data-driven cooperative intelligent controller was proposed in [4].

Certain biointelligent self-control processes are effectively mimicked by some biological intelligent controllers. As in the case of traditional controllers these bio intelligent controllers require specific mode of the plant to tune their control parameters. And thus their control efficiency depends on the accuracy of the derived plant model. It is somewhat easier to acquire running data for a plant in production process compared to its model. Using the available data in controlling the process rather deriving its model is a new research area and it is known as data driven control. The virtual reference feedback tuning (VRFT) is one among the data-driven control methods. VRFT solves a model-reference control problem without the need of any model of the plant. Based on an overall idea of controller parameters selection in [7] VRFT was proposed in [6].



In this brief, the transfer function of the conical tank is first derived. Then the performance of conventional controllers like P, PI and PID are studied. Then performance of intelligent controllers- fuzzy and DNUC are studied. Results of nonconventional and intelligent controllers are compared.

This brief is organized as follows. In Section II, the principle and mathematic foundations of data-driven neuroendocrine ultrashort feedback controller is introduced. In Section III an application example on conical tank process is given with its simulation results and analysis. Finally, conclusions are drawn in Section IV.

II. THEORETICAL FOUNDATIONS

A. Neuroendocrine Ultrashort Feedback Controller.

To improve the controller's performance NUC incorporates a biointelligent control unit with a conventional controller. The NUC method is the mathematical generalization and modification of the hormone regulation mechanism of human neuroendocrine system. The hormone regulation mechanism of human body is a well-preformed self-control process. In NUC the above mechanism is used to compensate a conventional controller. The basic structure of NUC control system is shown in Fig. 1. It consists of a control plant, an ultrashort feedback unit (UFU) and a conventional controller unit (CCU) [3].

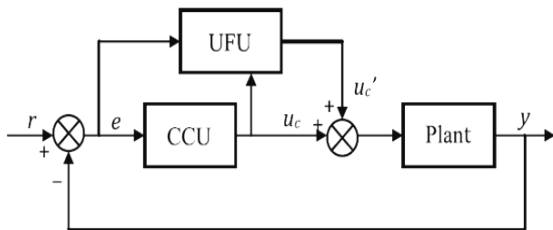


Fig. 1 Structure of the NUC control system.

According to the hormone regulation principle, the UFUs algorithm is written as given by [5]:

$$((u_c(k), e(k)) = \alpha \left[\frac{(\Delta u_c(k))^\xi}{1 + |\Delta u_c(k)|^\xi} + \beta \right] L_1 L_2$$

$$L_1 = \frac{e(k)}{|e(k)|} \times \frac{\Delta e(k)}{|\Delta e(k)|}, L_2 = \frac{\Delta u_c(k)}{|\Delta u_c(k)|} \tag{1}$$

Where $\Delta u_c(k)$, $k = 1, \dots, N$ is the variance of $u_c(k)$ and $\Delta u_c(k) = u_c(k) - u_c(k - 1)$. $\Delta e(k) = e(k) - e(k - 1)$. α , β , and ξ are all positive real numbers. The controlling direction factors L_1 and L_2 are used to eliminate the error effectively. They make sure that the output of the controller is always against the changing direction of the plant error. The output signal of the NUC is the sum of the CCU and UFU, which is

$$U_{NUC}(k) = U_c(k) + U'_c(k) \tag{2}$$

The control pattern constructed on the basis of neuroendocrine regulation principle can be treated as an accelerator for the conventional controller [4].

To ensure that $u'_c(k) = 0$ when $\Delta u_c(k) = 0$, the controller parameter β must be set to zero. The tuning of the vital parameters α and ξ is lack of theoretical assistance. In the existing studies of the NUC, tuning the two parameters was attained either by using optimization algorithm on plant's model with quantizing the control performance as optimization objective or repeatedly trying on the plant's model.

B. VRFT Method.

VRFT is a very convenient and efficient scheme among various data-driven algorithms. It is apt for the design of all types of parameterized controllers: $C(z; \theta)$ ($C(z; \theta) = \gamma^T(z)\theta$), including the proportional-integral-differential (PID) controller. Fig 2 shows the structure of the VRFT control system.

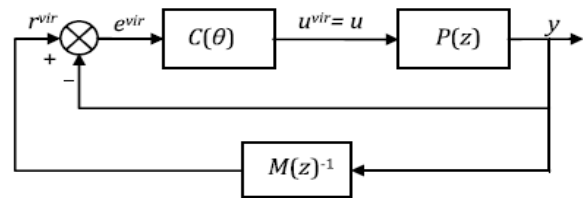


Fig2 Structure of control system based on VRFT method

In Fig 2, $\{u(t), y(t)\}$ is a set of measured I/O data of the plant $P(z)$ which means even if the $P(z)$ is unknown, we know that it will produce $y(t)$ when fed by $u(t)$. $M(z)$ is the preferred reference model for the closed-loop system to design. The $r^{vir}(t)$ is a reference signal that makes $y(t)$ be the desired output of the closed-loop system. So $M(z) r^{vir}(t) = y(t)$. Since $r^{vir}(t)$ is not an actual measurement data it is called virtual reference. Then, the notion is to search for a controller $C(z; \theta)$ that generates $u(t)$ when fed by the virtual corresponding tracking error $e^{vir}(t) = r^{vir}(t) - y(t)$. Since we know the signals $u(t)$ and $e^{vir}(t)$ searching of desired controller reduces to the identification problem of describing the dynamical relationship between them.

The above idea can be instigated by the following three-step algorithm (where a filtering of data through a user-chosen filter $L(z)$ is also considered). Given a set of discrete measured I/O data of $P(z)$: $\{u(k), y(k)\} k = 1, \dots, N$, do the following steps:

- 1) Calculate the virtual reference $r^{vir}(k)$ due to $y(k) = M(z) r^{vir}(k)$, and the corresponding tracking error $e^{vir}(k) = r^{vir}(k) - y(k)$;
- 2) Filter the signals $e^{vir}(k)$ and $u(k)$ with a suitable filter $L(z)$ $e_L(k) = L(z)e^{vir}(k)$, $u_L(k) = L(z)u(k)$;
- 3) Select the controller parameter vector θ_N , that minimizes the following criterion:

$$J_{VR}^N(\theta) = \frac{1}{N} \sum_{k=0}^N (u_L(k) - C(z; \theta)e_L(k))^2 \tag{3}$$



note that when $C(z; \theta) = \gamma^T(z)\theta$, (3) can be given the form

$$J_{VR}^N(\theta) = \frac{1}{N} \sum_{k=0}^N (u_L(k) - \phi_L^T(k)\theta)^2 \quad (4)$$

$$\phi_L = \gamma(z)e_L(k) \quad (5)$$

and the parameter vector θ_N is given by

$$\theta_N = \left[\sum_{k=1}^N \phi_L(k)\phi_L(k)^T \right]^{-1} * \left[\sum_{k=1}^N \phi_L(k)u_L(k) \right] \quad (6)$$

C. Data-Driven Improvement For NUC.

All kinds of conventional controllers can be taken as the CCU of the NUC. Due to the simplicity, accuracy and rapidity VRFT method is chosen to build a data-driven conventional controller. The specific implementation steps have been introduced in Section II-B. It is somewhat difficult and crucial to build up the nonlinear intelligent control unit UFU using only data due to the fact that the NUC is a biointelligent algorithm. The idea of VFTR is that it makes use of the measured data and reference model to obtain a set of virtual data. The measured data and virtual data are combined into a full I/O data set of the controller. The controller's structure and I/O data are used to tune the controller's parameters [1].

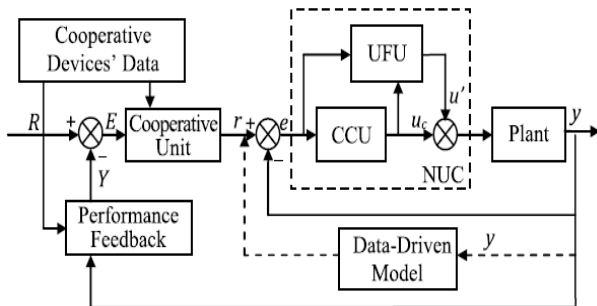


Fig 3 Structure of the DNUC control system

The first step in designing the DNUC is to build the CCU via VRFT method. Second step is to tune the UFU. The data used for tuning the UFU, is collected from the open-loop data of the plant and closed-loop system formed by the CCU and plant and. UFU unit is for improving the performance of the CCU. The tracking error can be used to tune the UFUs parameters.) .Only one closed-loop experiment of the plant controlled by the CCU is done to get a set of tracking error $e_{cl}(k)$. A set of I/O data of the closed-loop system: $\{r(k), y_{cl}(k)\}$ was attained

$$e_{cl}(k) = r(k) - y_{cl}(k). \quad (7)$$

Since the output of the UFU is used for compensating $e_{cl}(k)$ we give the UFU a virtual output $u_c^{vir}(k)$, which meets

$$e_{cl}(k) = P(z)u_c^{vir}(k) \quad (8)$$

Using the knowledge of the VRFT shown above, there is

$$M(z) = \frac{P(z)C(z)}{1 + P(z)C(z)} \quad (9)$$

Based on (7)–(9), $u_c^{vir}(k)$ can be rewritten as

$$u_c^{vir}(k) = \frac{1 - M(z)}{M(z)} C(z)(r(k) - y_{cl}(k)) \quad (10)$$

where both $M(z)$ and $C(z)$ are known and $\{r(k), y_{cl}(k)\}$ is the measured data.

With the input data of the UFU $[e_{cl}(k), u_c(k)]$, the desired output data of the UFU $[u_c^{vir}(k)]$, and structure of the UFU in (1), the parameters α and ξ of the UFU is to be chosen to minimize the following criterion:

$$J^N(\alpha, \xi) = \frac{1}{N} \sum_{k=1}^N (u_c^{vir}(k) - f_{UFU}(u(k), e_{cl}(k)))^2 \quad (11)$$

Since the UFUs algorithm is an intelligent one different from linear VRFT tuning method, an optimization algorithm can be used to solve the optimization problem in (11). There are many optimization methods, such as genetic algorithm or particle swarm optimization algorithm. Anyone of them can be used to optimize the above problem.

At this point, the original biointelligent control method NUC has been modified to become the DNUC method.

III.SIMULATION RESULTS

A. Conical Tank Process.

The system to be controlled is a conical tank system in which the height (level) of the liquid inside the tank is to be kept constant irrespective of the inflow and outflow rate. The constant level of the liquid is maintained by adjusting the inflow rate to the system by adjusting the control valve position. The specifications of the conical tank are

- Height, H : 70cm
- Steady state value, h : 10cm
- Bottom radius, r : 2cm
- Top radius, R : 17.6cm

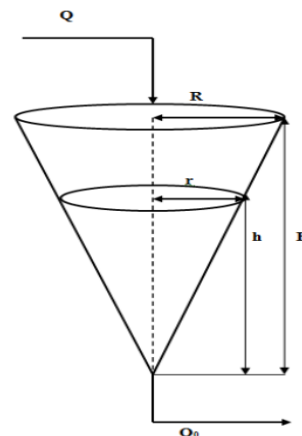


Fig. 4 Conical tank



In the above figure ‘Q’ represents flow rate of the inlet stream, ‘Qo’ represents flow rate of the outlet stream, ‘R’ indicates maximum radius of the conical tank, ‘r’ for radius of the conical tank at steady state, ‘H’ stands for maximum height of the conical tank and ‘h’ represents height of the conical tank at steady state.

According to mass balance equation,
Accumulation = Input- Output

$$A \frac{dh}{dt} = Q - Q_o \tag{12}$$

$$Area, A = \pi r^2 = \pi \left(\frac{Rh}{H}\right)^2 \tag{13}$$

So that the tank model becomes,

$$\frac{dh}{dt} = \frac{\alpha Q}{h^2} - \beta h^{-3/2} \tag{14}$$

Where α and β are parameters defined by,

$$\alpha = \frac{1}{\pi} * \left(\frac{H}{R}\right)^2 \tag{15}$$

$$\beta = c\alpha \tag{16}$$

Here, Q is the inlet flow rate, the manipulated variable. This process model has two types of nonlinear functions: Q_h^{-2} , a product of two functions, and $h^{-3/2}$. These two functions have to be linearised. Linearization is the process by which a nonlinear system is approximated to a linear process model. The most popular technique for obtaining the linear approximation is based on Taylor series expansions of the nonlinear aspects of the process model. The linearization of $f(h, Q) = Q_h^{-2}$ proceeds as follows,

$$f(h, Q) = f(h_s, Q_s) + \frac{\partial f(h-h_s)}{\partial h} + \frac{\partial f(Q-Q_s)}{\partial Q} + \text{Higher terms}$$

Ignore the higher order terms,

$$h^{-(3/2)} = h_s^{-(3/2)} - \frac{3}{2} * h_s^{-(5/2)} * (h - h_s) \tag{17}$$

Under steady state condition, $\alpha Q_s = \beta h_s^{1/2}$. Now introduce the variables $y = (h - h_s)$ and $u = (Q - Q_s)$. The approximate linear model is obtained as,

$$\tau * \frac{dy}{dt} + y = Ku \tag{18}$$

Where the steady-state gain, and time constant associated with this approximate linear model, are given by,

$$K = \frac{2\alpha}{\beta} * h_s^{1/2} = \frac{2}{c} * h_s^{1/2} \tag{19}$$

$$\tau = \frac{2}{\beta} * h_s^{5/2} \tag{20}$$

Applying the values for all the parameters and taking Laplace transform, the conical tank transfer function is obtained. Once the transfer function is obtained, then the controller can be designed for the conical tank process.

The system transfer function is obtained as first order process.

$$G(s) = \frac{3.184}{62.81s+1} \tag{21}$$

B. Conventional Controller Simulation.

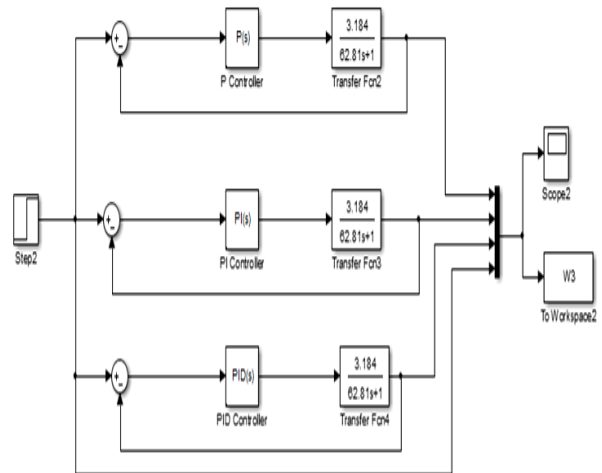


Fig. 5. System with conventional controllers

Simulink model of the conventional controller and the plant with unity feedback is shown in Fig.5. Ziegler – Nichols Tuning method has chosen to design the controller for conical tank system. Among the two methods consisting of open loop response method and closed loop response method, open loop response method has chosen as it is less complicated and ease in calculation. Steady state value (K) is calculated by applying a step input to the transfer function of the conical tank system.

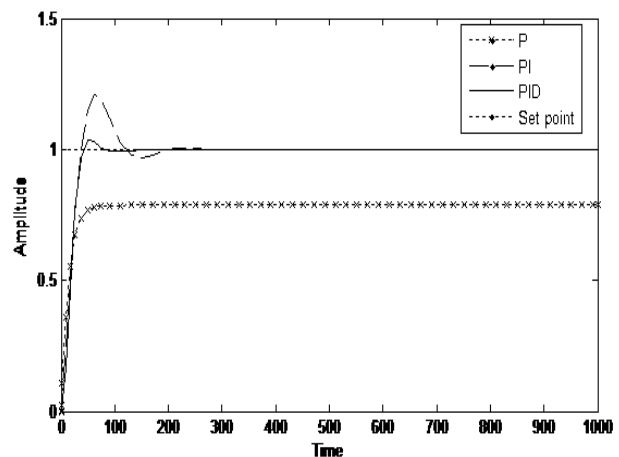


Fig. 6. Step response with conventional controllers

It is observed that the closed loop response of the system for a P controller has a constant value but offset is too large from set point. PI controller has reached the set point but the time taken to reach the steady state value is comparatively large. But PID controller can acquire the set point with the shortest time period and so PID controller is



ideal for this application as compare with the other two controllers.

C. Fuzzy Logic Controller Simulation

The Fuzzy Logic Controller has two input variables, namely the error and the change in error and the output is control action. The membership function of the input and output variables are labeled as: Negative Big (NB), Negative Small (NS), Absolutely Zero (AZ), Positively Small (PS) and Positively Big (PB). Steady state value (K) is calculated by applying a step input to the transfer function of the conical tank system. Simulink model of the conventional controller and the plant with unity feedback is shown in Fig.7.

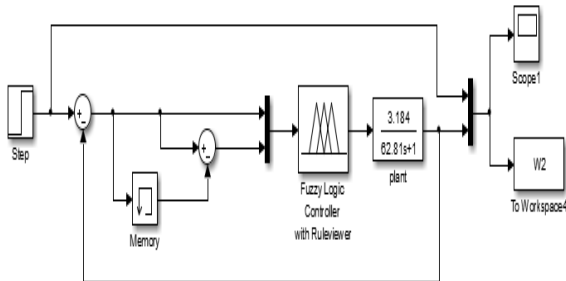


Fig. 7. System with fuzzy logic controller

From the step response of the system with fuzzy controller it is observed that the closed loop system with fuzzy logic controller attains the steady state value quicker than the conventional controllers and also it does not introduce any overshoot. Even though the FLC has advantage of low steady state time, set point is not at all reached. Fuzzification of inputs is to be done manually. Also the performance of the controller depends on the number of rules in the fuzzy rule base.

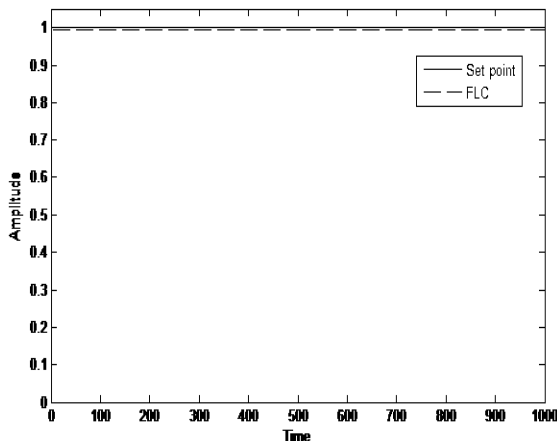


Fig. 8. Step response with fuzzy logic controller

D. DNUC Simulation

To tune the controller, the CCU is firstly tuned by the standard VRFT. As the standard VRFT steps, a set of plant's open-loop I/O data is collected before the tuning calculation. After the tuning calculation, the desi.gned

CCU is then put into closed-loop running. Another set of test data is collected from this closed-loop system. In addition, with the performance data of the CCU, the parameters of the UFU are tuned. Simulink model of the DNUC and the plant with unity feedback is shown in Fig.9.

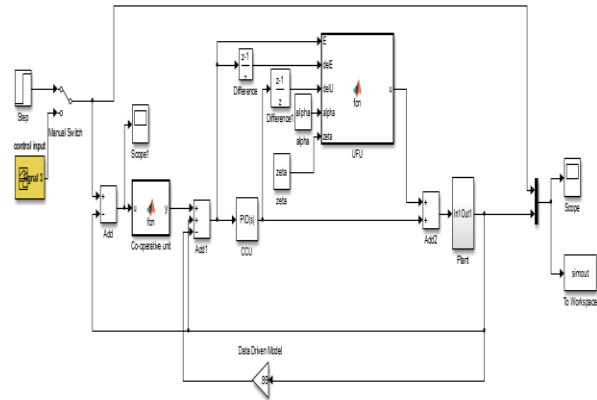


Fig. 9. System with DNUC

Step response of conical tank process is obtained. The set point is attained without any overshoot. Response of the DNUC controller is much better than the conventional controllers and FLC.

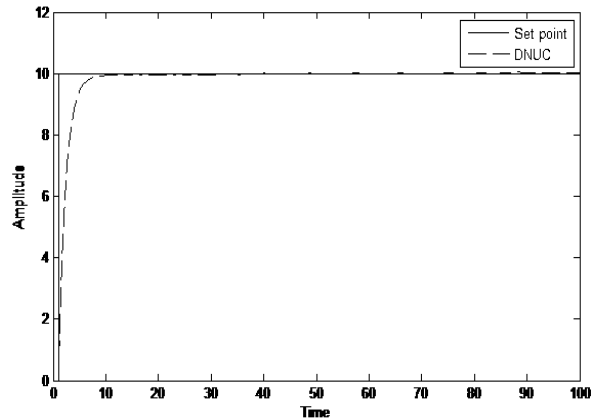


Fig. 10. Step response with DNUC

TABLE I TIME RESPONSE PARAMETERS

	Mp(%)	t _s (sec)
P	0	52.4
PI	21.2	173
PID	3.59	65.8
FLC	0	2.3
DNUC	0	5.6

IV. CONCLUSION

Performance analysis of DNUC controller for a conical tank processes is done. Simulation results are taken using MATLAB-SIMULINK. Comparison of DNUC with a fuzzy logic and conventional controllers such as P, PI, and



PID gives testimony to the effectiveness of the DNUC in the non-linear system. Experimental results prove that the response is smooth for DNUC compared to conventional controllers. The settling time and percentage overshoot in the DNUC show the better response than conventional controllers. The performance of DNUC is much higher than FLC. It is concluded that for a nonlinear system the DNUC outperforms well when compared to conventional controllers and Fuzzy Logic Controller.

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