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Intelligent Control of pH in a Neutralization Process

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Abstract: In the present study, control of pH neutralization process using neural and fuzzy controller is proposed. Initially a conventional PI controller based on the Relay Feedback method is tried to control the pH at different linear regions. Control of pH by conventional PI controller based on the local linear model fails to provide satisfactory performance over the entire region. Hence to overcome this drawback a Neuro controller with inverse model anticipation and a fuzzy controller are used. In this study, a novel fuzzy controller is used. Most fuzzy controllers use control error (e) and change in the control error (Δe) as controller inputs and not able to differentiate the region in which process operates. This controller uses set point as third input to select the region in which the process is operating. An experimental study of the performance of the intelligent controllers designed is carried out on a pilot plant in the lab.

Key words: Relay feedback, neural network based controller, fuzzy controller, neutralization process, pilot plant

INTRODUCTION

The control of pH is one of the most difficult challenges in the process industry because of the severe nonlinearities in the behaviour of the system. It plays an important role in neutralizing excess reagents, acidic by-products and obtaining high yield of selective products. The pH process can be classified as continuous process, batch process or fed batch process. Model based non linear controllers are suitable for this type of process when compared to conventional controllers (Bharathi *et al*., 2006). The continuous type pH process is usually modeled as a first order plus time delay model around the nominal operating point. The steady state gain shows significant variation with the change in the operating point. This makes it difficult to design a single linear controller to perform satisfactorily in all the regions.

Modeling of the pH process is supposed to be a difficult task because one needs to have knowledge about the components and their nature in the process stream in order to model its dynamics. McAvoy *et al*. (1972) developed a model for the pH neutralization process with a single-acid single base system. This particular model has been widely accepted in the literature. Gustafsson and Waller (1983) generalized the model for a pH system with an arbitrary number of acids and bases using the reaction invariant concept.

The performance of proportional integral controllers for the pH neutralisation process has been studied and reported in literature. As the process dynamics around an operating point can be represented by a first order plus time delay model, conventional proportional integral controllers has been tried. But the performance of these controllers is not good with change in operating point and process parameters. Different approaches for pH control are proposed in the literature. Shinskey (1988) has proposed several approaches for the effective control of pH (1988). Wright and Kravaris (1991) have proposed nonlinear control of pH. Gupta and Coughanower (1978) have used adaptive PI schemes for overcoming the gain variations. But this method is a time consuming process of titration curve identification by different methods.

Different fuzzy controllers have already been developed in the literature. Biasizzo *et al*. (1997) have proposed predictive control based on a fuzzy model, where the algorithms for linear processes are ex-tended to the nonlinear process. A similar idea has been proposed by Sing and Postlethwaite (1997), using a fuzzy relational model and a predictive controller. In Edgar and Postlethwaite (2000) a technique to construct a relational model from a fuzzy input space to a crisp output space, evaluating the relation by application of a least-squares identification technique to process past data, has been

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presented. Babuska *et al.* (2002) have proposed a fuzzy self-tuning proportional integral controller for a pH control in a fermentation system, where the essential idea is to tune the controller gains on-line by means of a parameter that results from a fuzzy inference mechanism. Other fuzzy controllers developed in the literature for different systems are by Sousa *et al.* (1997) where a method of designing a non-linear predictive controller based on a Takagi-Sugeno fuzzy model of the process has been proposed. This fuzzy model, calculated with an identification technique that enables the acquisition of the fuzzy model from process measurements, was incorporated as a predictor in a nonlinear based-model predictive controller using the internal model control scheme to compensate for disturbances and model errors. Simulation study is carried out on novel fuzzy controller which uses setpoint as the third input and this controller is used to control a pH neutralization process (Bharathi *et al.*, 2006).

In the present study proportional integral controller for local linear models and their drawbacks are studied and intelligent controllers are used for the same process to show how they overcome the drawbacks in the proportional integral controller.

PROCESS DESCRIPTION

The system under consideration is a continuously stirred tank reactor, in which a weak acid (Acetic acid) is neutralised by adding a strong base (Sodium Hydroxide) continuously. The flow rate of strong base is manipulated to get the required pH. Material and ionic balance gives a set of linear differential equations and nonlinear static equation:

$$V\frac{dx_a}{dt} = F_aC_a - (F_a + F_b)x_a \tag{1}$$

$$V\frac{dx_b}{dt} = F_bC_b - (F_a + F_b)x_b \tag{2}$$

$$x_b - \frac{x_a}{\left(1+10^{(pK_a - pH)}\right)} + 10^{-pH} - 10^{pH-pkw} = 0 \tag{3}$$

(Ka-Dissociation constant of the weak acid is 1.83×10^{-5}). With the electro neutrality equation.

$$[Na^+] + [H^+] = [Ac^-] + [OH^-] \text{ where} \tag{4}$$

$$[H^+]\,[OH^-] = K_w \tag{5}$$

Where x_a and x_b are state variables, V is volume of the reactor, Fa is Flow rate of acid, C_a is concentration of acid, C_b is concentration of base, K_w is equilibrium constant for water dissociation at 25°C, F_b is the manipulated variable and pH is the system output. The steady state characteristic titration curve (Fig. 1) for the acid base system is generated for change in the base Flow rate (Fb) from 0-25 Lh^{-1}. The titration curve is divided in to different linear zones. For this process, three regions of nonlinear gains can be identified: pH-High, pH-Middle and pH-Low.

Design of local linear PI controller: As discussed in the previous section, the steady state curve is divided in to three zones and a local linear controller is designed for these three zones. The design of controllers requires identification of the transfer function model of the process, which can be carried out either by open loop method or closed loop method. Closed loop identification is preferable since the method is insensitive to disturbances and measurement noise. Relay feedback test is a closed loop test. The shape information from the relay feedback test is used to identify the correct model structure, to estimate the correct model parameters and hence to find the appropriate Proportional-Integral (PI) controller settings.

Relay Feedback test (RFB): Figure 2 shows the block diagram of the relay feed back system. Astrom and Haggalund (1984) proposed that, when the relay output lags behind the input by -π radians, the closed loop system oscillates with a period of P_u, around the set point. A relay of magnitude h is inserted in the feedback loop. Initially, the input u(t) is increased by h. When the output y (t) starts increasing after a time delay D, the relay switches to opposite direction, u (t) = -h. Since there is a

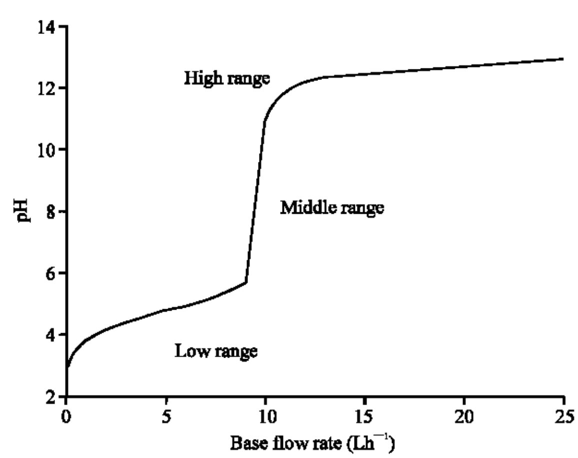

Fig. 1: Steady state titration curve

phase lag of -π, a limit cycle of amplitude a is generated (Fig. 3).The period of the limit cycle is the ultimate period, P_u. The ultimate frequency $(\omega)_u$ can be found using (6). From the principle harmonic approximation of the oscillations, the approximate value of ultimate gain (K_u) can be derived and is given in (7).

$$\omega_u = \frac{2\pi}{Pu} \quad (6)$$

$$K_u = \frac{4h}{Pu} \quad (7)$$

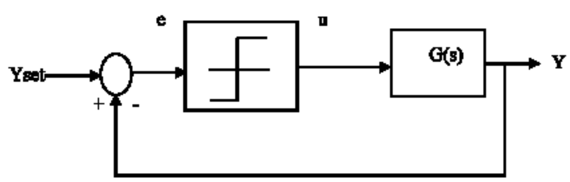

Fig. 2: Block diagram of relay feedback system

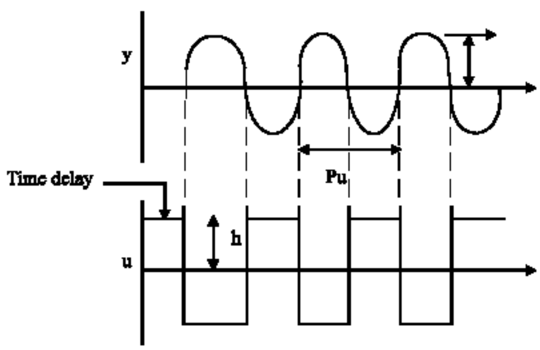

Fig 3: RFB test for a system with positive steady-state gain

With the above values using Ziegler-Nichols tuning method, the PI controller settings for the three regions is found out.

$$Kc = \frac{K_u}{2.2} \quad (8)$$

$$T_I = \frac{P_u}{1.2} \quad (9)$$

In the regions of pH-High and pH-Low the process gain is extremely small, i.e., the base flow rate must make a big change to make a significant change in the pH value. On the other hand, in the pH-Middle region the process gain is extremely high, i.e., a small change in the base flow rate would result in a large change in pH value.

REAL TIME IMPLEMENTATION OF RELAY FEEDBACK IDENTIFICATION AND CONTROL

The hardware setup consists of a process tank made of borosil glass whose volume is 5.7 L. Magnetic stirrer is provided to stir the contents of the process tank to have uniform pH. The process setup employs supply tanks each for an acid and a base. These tanks are provided with outlets that lead to the process tank via the control valves. A combined glass electrode is used to measure the pH value online. The pH sensor is placed in the process tank near its outlet. The pH sensor gives a voltage corresponding to the measured pH value in the process tank that is converted to a standard range of (4-20) mA by the online industrial pH transmitter. There are 2 control valves to control the flow rate of acid or the base (Fig. 4).

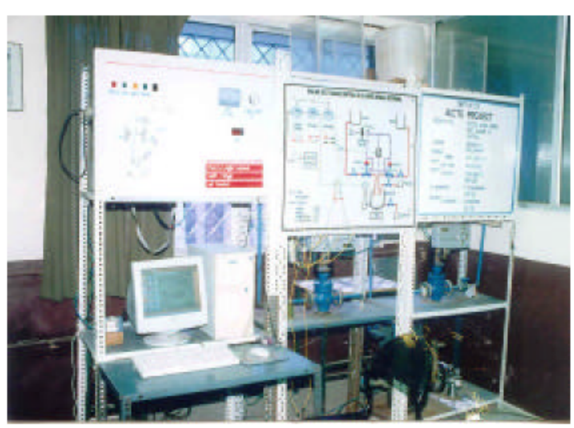

Fig. 4: Lab scale experimental set up

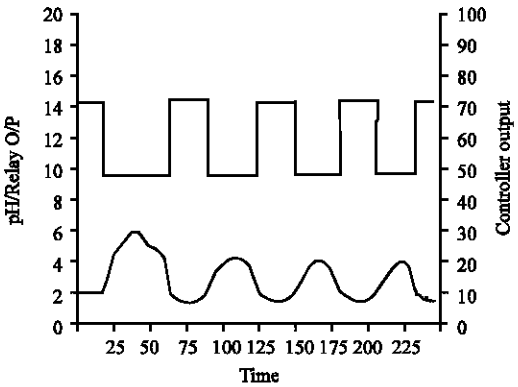

Fig. 5: RFB test for pH-low

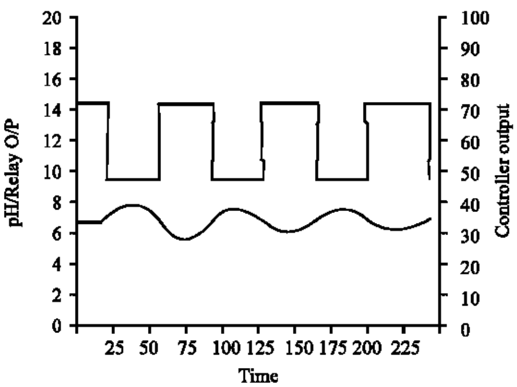

Fig. 6: RFB test for pH-middle

The logic for identification is implemented using algorithm written in C language. A relay has positive and negative half cycles. The output of the relay is decided based on its input. If the input exceeds the set point, positive half cycle occurs and on the other hand, the negative half cycle results. In this setup, where in a split range operation of valves is used, the positive part is taken as the base region and the negative part is taken as the acid region. The manipulated variable here is the flow rate of acid or base, therefore, the height of relay (h) depends on the % opening of the valves. From the response, ultimate period (Pu), time delay (D) and output amplitude (a) are measured to calculate the ultimate gain (Ku), ultimate period (ωu). Time constant, static gain and time delay represent the first order plus time delay model. The real time relay feedback responses are shown in the Fig. 5 and 6 (Upper Square wave represents relay output and lower sine wave like represents the plant response).

The proportional integral controller settings designed based on the model parameters are used to control the process at three operating zones (Table 1). Figure 7and 8 show the closed loop response of the process. Set point pH value for zone 1 and 2 are 2.5 and 7, respectively. From the response, it is understood that the relay feed back method is a simple and efficient way for model identification which is used to design the local linear controllers. But these local linear controllers will not perform better when the set point switches to other regions. Hence the intelligent controllers are used (Fig. 7 and 8).

Table 1: Linear model and PI controller parameters in various zones (D = 20 min)

Zone	Pu	h	a	K_p	τ	Kc	Ti
pH-low	65	0.04	1.03	57	27.2	0.014	25
pH-middle	68	0.01	1.03	258	38	0.003	35
pH-high	68	0.015	0.3	57	38	0.024	35

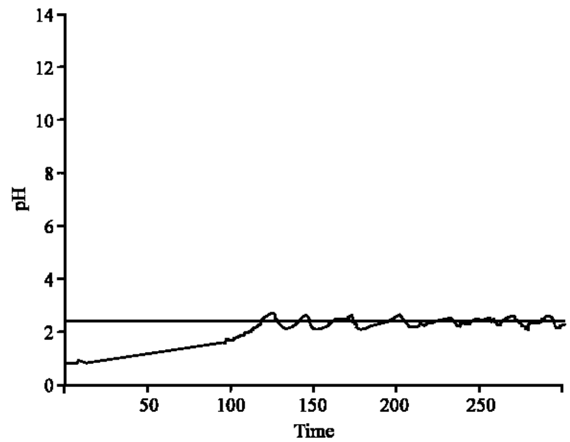

Fig. 7: Closed loop response in pH-low zone

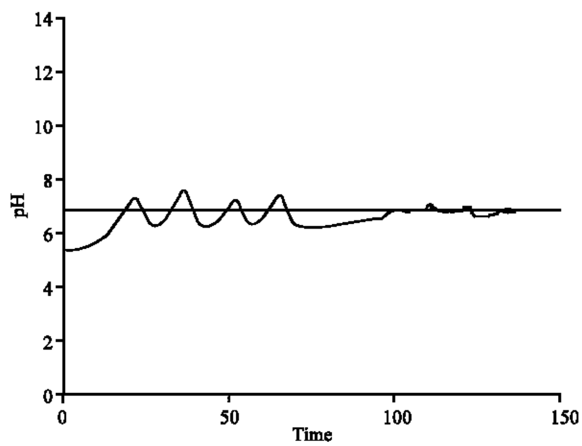

Fig. 8: Closed loop response in pH-middle zone

FUZZY LOGIC CONTROL SCHEME

To eliminate the drawbacks of conventional control a fuzzy controller is designed and implemented. Most fuzzy controllers use control error (e) and change in the control error (Δe) as controller inputs. However, it was experimentally shown in the pH processes that when using only these inputs the fuzzy controller is not able to differentiate the region in which the process operates, which is important information, necessary to control the nonlinear process. Therefore, such fuzzy controllers cannot make a control action based on the knowledge of the process nonlinearity associated with different regions. In this study a multiregional fuzzy controller is used, following the ideas of Qin and Borders (1994). This controller uses, an additional input, the set point, to indicate in which region the process operates. Such fuzzy controllers can compensate the process nonlinearity, so the control performance is more uniform and this controller is a general solution for systems with a high and smooth nonlinearity with respect to different regions of operation.

To design a fuzzy controller that gives satisfactory performance for different regions of gain nonlinearity, a fuzzy controller with three inputs is used to allow different control strategies to be designed in different regions. In addition to using the control error (e) and change in the control error (Δe) as inputs, set point is used as another input as shown in Fig. 9, to select the region in which the process is operating. The functional relationship of such a controller can be described by:

$$u = f(e, \Delta e, SP) \qquad (10)$$

Where f (.) stands for the nonlinear relationship of the fuzzy controller. Instead of set point, the control variable or the process output can be used as the third input to the fuzzy controller depending on how the operation regions are defined. Given a particular set point, the fuzzy controller can be designed based on the process knowledge associated to that region, as a classical fuzzy PI-type controller.

From the closed loop response, the error, change in error and controller output data for various set points is collected using conventional PI controller settings designed for the three linear regions. Next, it is necessary to define the fuzzy membership functions associated with the controller inputs: The control error and the change in the control error and with the controller output based on data collected using PI controller. The membership functions for the error, change in error is 5 and controller output is 7 as NL (Negative Large), NS (Negative Small), NM (Negative Medium), ZE (Zero), PS (Positive Small), PL (Positive Large). The next step is to define the fuzzy rule knowledge.

A general fuzzy inference rule for this controller that has three inputs and a single output as:

R_i: _If SP is A_i and e is B_i and Δe is C_i then u is D_i, where Ai, B_i, C_i and Di are adjectives for the Set Point (SP), the

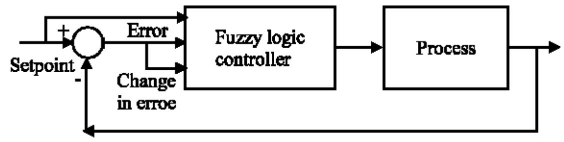

Fig. 9: Block diagram of fuzzy logic controller

Table 2: Rules for the fuzzy logic controller

e	Δe NL	NS	ZE	PS	PL
SP = Low					
NL	PL	PL	PL	PM	ZE
NS	PL	PL	PM	ZE	NM
ZE	PM	PM	ZE	NM	NL
PS	PS	ZE	NM	NL	NL
PL	ZE	NS	NM	NL	NL
SP = Medium					
NL	PM	PM	PM	PS	ZE
NS	PM	PM	PS	ZE	NS
ZE	PM	PS	ZE	NS	NM
PS	PS	ZE	NS	NM	NM
PL	ZE	NS	NM	NM	NM
SP = High					
NL	PL	PL	PM	PS	ZE
NS	PL	PL	PM	ZE	NS
ZE	PL	PM	ZE	NM	NM
PS	PM	ZE	NM	NL	NL
PL	ZE	NM	NL	NL	NL

error (e), the change in the error (Δe) and the control action (u), respectively. It is necessary to define a set of fuzzy rules for each process region. In this application, set point has adjectives low and high and medium. The final set of fuzzy rules for the pH neutralization process is shown in Table 2. These rules can be interpreted as: If SP is medium and e is PL and Δe is PL then u is NM.

The above defined fuzzy controller has been implemented using the fuzzy Logic Toolbox of MATLAB. To examine the control performance over all regions, the set point of pH is changed from 4-6, 6-7, 7-9 (positive step change) and 9-7, 7-5 (negative step change). Figure 8 depicts the dynamic response when the set point changes and 9 shows the control actions. It can be seen that positive step changes in different gain zones gives different time responses and different behaviour. When the step change is in the middle region (particularly near the equivalence point where pH = 7) more oscillation appear. However, when the step is in the low-gain zone there is no oscillation. As a consequence, it is possible to conclude that this fuzzy controller performs well in all the desired operation regions.

NEURAL NETWORK BASED CONTROL SCHEME

In the previous approach, from the available human knowledge, rule base and membership functions are formed which do not give accurate control. Instead of that

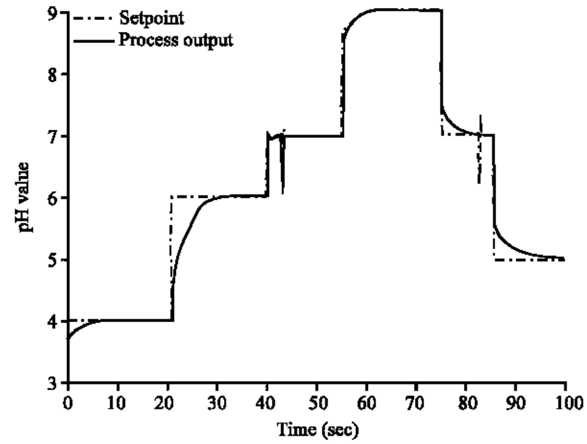

Fig. 10: Process response with set point change

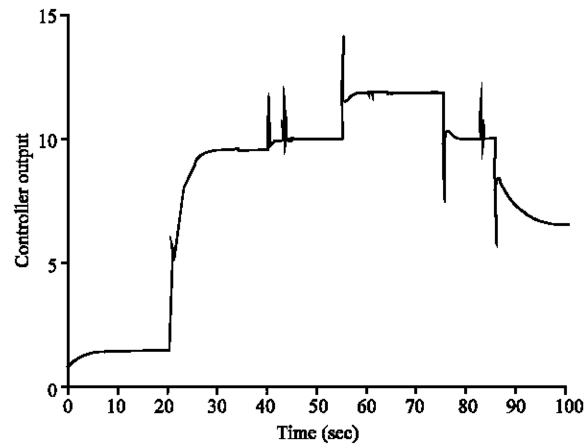

Fig. 11: Controller output

the neural networks are used which does the exact input-output mapping and thus gives accurate control. Since the process under study is a highly nonlinear process, neural network controller is tried as it is considered to be good for nonlinear time varying processes.

The open loop test on the real time process is conducted by varying the base flow rate (manipulated variable) in steps of 0.5 from 0-25, the corresponding pH value (controlled output) is noted down (Fig. 10 and 11). With the above noted readings, the network is trained using back propagation algorithm in such a way that it will be able to generalize any input within this range, with which it was not trained earlier. The architecture of neural network has one input neuron, 7 hidden neurons and one output neuron. After framing the architecture, next step is to train the network. By using the nntool in MATLAB it is carried out. The neural network is trained in such a way that the pH value acts as the input to

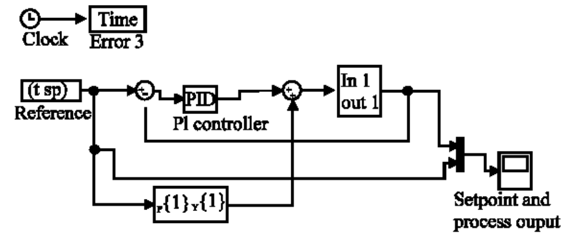

Fig. 12: Neural network based controller with inverse model anticipation

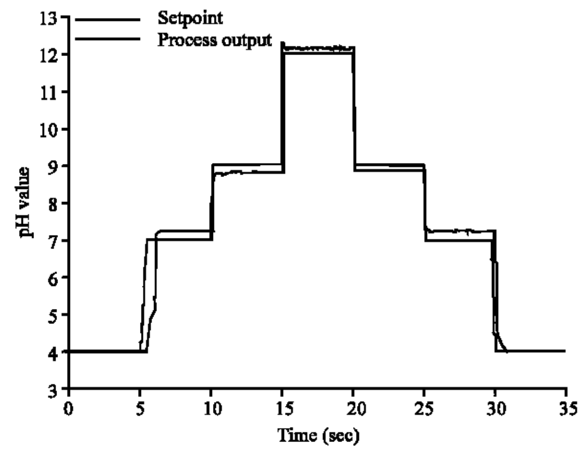

Fig. 13: Set point tracking of the NN based controller

the model and manipulated variable (base flow rate) as the output. Hence the model is called as the inverse model (Fig. 12). After training and validation, the inverse neural network model of the pH process is used to control the pH value. Figure 13 shows the set point tracking of the designed neural network based controller.

CONCLUSION

For a pH process, the design of local linear controller using relay feedback, design of neural network controller and a novel fuzzy controller which uses three inputs to generate one control signal were discussed in this study. The three inputs are control error, the change of the control error and set point to indicate different non-linear regions of the process. This third input set point enables the controller to give better control performance. The results obtained show that the performance of this fuzzy controller is good to control highly nonlinear processes. The performance of the neural network based control is better than that of fuzzy controller. The results clearly show that the limitations of linear PI controller are eliminated with the help of intelligent controllers. It is studied that no single linear controller can able to give better performance over the entire range of the steady state curve of the process where as an intelligent controller is able to give satisfactory performance over the entire range.

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