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Modeling and Control of Non-Linear CSTH Process using Hybrid Optimized Technique

R Dhanasekar[1]* & S Vijayachitra[2]

[1]Department of Electronics and Instrumentation Engineering, Bannari Amman Institute of Technology, Anna University, Erode 638 401, India

[2]Department of Electronics and Instrumentation Engineering, Kongu Engineering College, Anna University, Erode 638 060, India

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The highly non-linear Continuous Stirred Tank Heater process (CSTH) is modeled using appropriate process dynamics by considering multivariable factors in all chemical industries using Multi-Input Multi-Output (MIMO) system to prepare an extremely saturated solution with the required conditions. The model's transfer function and state space are created by applying the first principle method to successfully regulate the Level and Temperature of the CSTH process using specified time-domain parameters and a suitable conventional Proportional Integral Derivative (PID) controller. The Ziegler-Nichols method aims to estimate gain factor for controller. However, more effective and efficient control of the process is still required. Advanced optimization approaches such as Genetic Algorithm, Pattern Search, Fmin Search, and Hybrid Optimization Algorithm are more commonly used to fine-tune the controller's gain factor. Finally, a quantitative example is provided using a MATLAB simulation result to highlight the benefits and applicability of the proposed approach. The obtained result is validated by the experimental data from the real-time Process.

Keywords: Fmin search, Genetic algorithm, Multiple input multiple output, Pattern search algorithm, PID controller

Introduction

Controlling multivariable factors to boost the system's productivity in both quantitative and qualitative dimensions is a difficult task in the bioprocess industry. Insignificant process sectors such as the chemical and pharmaceutical industries. Continuous Stirred Tank Heater process (CSTH) is a very complicated multivariable system. Anbu *et al.*[1] influence the open-loop behavior and modeling of highly non-linear CSTH process with energy and mass balance around the cooling jacket. All the requirements listed above emphasize the importance of endless observation and external intervention in ensuring that a chemical plant's operational goals are met. This is accomplished by meticulously and carefully arranging various equipment, such as determining devices, regulators, controllers, computers, and human intervention (plant). Coldwater intake, hot water inlet, and inlet steam temperature are the inputs to this process. In CSTH, level, and outlet steam temperature are the output parameters that must be controlled. Before attempting to manage process, it is necessary to model the system by first-principles techniques for further analysis. Because of their simple designs and resilience behavior, Proportional Integral Derivative (PID) controllers have been frequently preferred in process industries for regulatory and servo tracking purposes over advanced control approaches such as Model Predictive Control, Fuzzy, Neural Modeling Adaptive Control, and so on. Selvaraj and Nirmal kumar[2] expressed the implementation of modelling and Genetic Algorithm-based optimization controller techniques for nonlinear conical and spherical tank systems and they have dynamic behavior nominated by the system parameters. The nonlinear process modeling and identification over its wide operating region play a dynamic role in controller performance and its design due to variations in operating conditions from time to time. The multiple model technique was established by dividing the entire operating region into different subregions and further tuning the conventional PID controller for each sub-region and also to avoid these challenges in nonlinear system modeling.

Literature Survey

Nina *et al.*[3] described that the University of Alberta simulated a continuously stirred tank heater pilot

*Author for Correspondence
E-mail: dhanasekar1693@gmail.com

plant. Sensor, actuator, process nonlinearities, as well as heat and volumetric balances, have all been extensively measured to account for the capacity engaged by reheating coils in the tank. They showed results from step tests as well as recordings of real-world disturbances. Ahmed and Ali[4] designed and simulated water level and temperature controller by a Proportional Integral Derivative (PID) Controller and a Fuzzy Logic (FL) Controller with two different PID controllers for controlling temperature and flow respectively. Alexandrov and Palenov[5] considered the plant as first-order time delay. In which coefficients of the plant are unidentified, and can adjust at any time. In the occurrence of unidentified external disturbances, self-tuning of the PID-I controller of the plant has been outlined. Several PID tuning techniques are being reported by Prakash and Srinivasan[6] including the Ziegler–Nichols (Z–N) method, Cohen–Coon (C–C) method, Internal Model Control (IMC) method, and Gain-Phase margin (G-P) method, with ISE, IAE, and ITAE to reduce the objective function. Prakash and Senthil[7] describe the design of an observer for a nonlinear CSTR processing MPC controller. The Genetic Algorithm for identifying system models and controller tuning has been described by Valarmathi *et al*.[8] Greater convergence and optimal values must be correctly selected in order to get greater convergence. Vijayakumar and Manigandan[9] proposed the use of an Enhanced Genetic Algorithm (EGA)-based suitable PID controller for nonlinear dynamic process control (CSTR). Result is validated by comparing the simulation results and the error performance criteria. Rajesh and Tamilselvan[10] obtained the mathematical model of the spherical tank through an open-loop experimental test in Mathematical Modelling and Measurable Design of an Industrial Nonlinear Storage Tank Level Control Process Feedback. The step response analysis was carried out utilizing transfer function and tank's state-space model. Model validation has been investigated in terms of process dynamics. Arunjayakar and Tamilselvan[11] presented numerous effects of disturbances and uncertainties on process dynamics, as well as innovative parameter optimization techniques, and analysed performance of system using GA-based PID and Conventional PID Controller. The above literature paper can be partitioned into four sections as follow. The first part briefly discussed modeling the Non-Linear Multiple Input and Multiple Output (MIMO) processes with and without disturbance. Based on this reference in view of adding novelty, the model of the real-time CSTH process for the operating region is developed. Experimental data was obtained and validated in a real-time setup. The second part details on design of the controller for process. Where above all work describes the importance of the PID controller and tuning controller by different techniques. Thus the present article replicates the design of the PID controller for obtained model and parameters have been tuned by the ZN method. Finally, the last part deals with the optimization of the controller to increase the stability of the system. The above-all work reinforces the conventional optimization algorithm like GA, PSO, and other techniques. In this paper, the obtained model through experimental data is validated by the above-discussed controller algorithms, and also to improve the novelty of the work, the advanced novel optimization methods like Hybrid (Pattern search + Fmin search) and Hybrid (GA + Pattern search + Fmin search) is introduced. The result obtained in MATLAB by implementing in real-time setup is analyzed (Comparative analysis) and evaluated based on time-domain specifications and performance error criteria to prove that the proposed hybrid optimized controller designed in this paper performs better and higher, compared to all techniques discussed.

Process Description

The Continuous Stirred Tank Heater is a technique that uses a continuous speed stirrer to thoroughly mix hot and cold water at the intake. The steam produced by the heating coil is utilized to further warm the mixer. The tank's blended liquid is then drained via lengthy conduct. The temperature of the flow in output is determined by the liquid temperature in the tank. Hot and cold water flow, CSTH tank level, and temperature in exit flow are all measured and controlled using appropriate sensors. In Fig. 1 the CSTH physical setup in real time is depicted. The CSTH plant's complete specification is shown in Table 1.

Mathematical Modeling of CSTH

The modeling of a real-time nonlinear process is required for predicting system dynamics using frequency and time domain specifications. Thus, by

Fig. 1 — Real-time setup of CSTH process

Table 1 — Specifications of CSTH

Equipment	Specifications
CSTH tank	Stainless steel body, height:60 cm, Diameter: 25.78 cm. Shape: cylindrical
Level transmitter	Input: 3–15 psi Output: 4–20 mA
Stirrer motor	RPM: 6000, Frequency: 50 HZ
Control valve	Size 1/4 Pneumatic actuated, Type: Air to open, Input: 3–15 psi
Rotameter	Input: 3–15 psi, Range:0–460 LPH
SCR	Output: 4–20 mA

evaluating the mass transfer, energy transfer, and mass flow of the entire physical process, the mathematical modeling of CSTH is identified using the first principle method. The piping and instrumentation system of the CSTH process is depicted in detail in Fig. 2.

Modeling with respect to Mass Balance and Energy Balance Equation

By studying mass and energy balance equation, first principle shall be used to model the CSTH using Eqs 1 to 8 below. The CSTH's layout as well as the specifications is depicted in Fig. 3. The input variable for the system is

- The tank's cold and hot water inlet flow
- Tank's steam flow

Meanwhile, the CSTH output variables are as follows:

- The liquid temperature at the outlet
- Tank Level

Heat transfer from tank to jacket can be described,

$$Q = U.A(T_j – T_t) \quad \ldots (1)$$

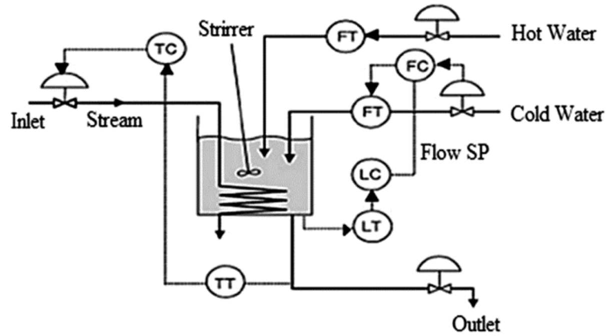

Fig. 2 — Piping and instrumentation layout for CSTH system

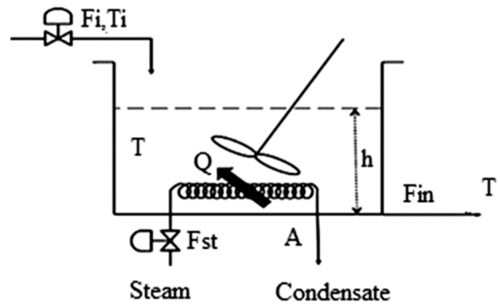

Fig. 3 — CSTH outline view with specifications

Mass balance around CSTH tank is first explained as follows,

Rate of accumulation = Inlet flow rate – Outlet flow rate

$$\frac{d\,(V\rho)}{dt} = F_i\rho - F\rho \quad \ldots (2)$$

Second, the material balance around the CSTH tank is given as,

$$\frac{d(V_j\rho)}{dt} = F_{ji}\rho - F_j\rho_j \quad \ldots (3)$$

Finally, the Energy balance of CSTH is written as,

Rate of Accumulation of Energy = Inlet Heat – Outlet Heat + Flow rate of Heat

$$V_t\rho_t Cp_t \frac{dT_t}{dt} = \rho_t F_t Cp_t T_i - \rho_t F_t Cp_t T_t + Q \quad \ldots (4)$$

Energy balance around the jacket of CSTH

$$V_j\rho_j Cp_j \frac{dT_j}{dt} = \rho_j F_j Cp_j T_{ji} - \rho_j F_j Cp_j\ T – Q \quad \ldots (5)$$

Therefore, the mathematical equations of CSTH are,

$$\frac{dT_t}{dt} = \frac{F_t}{V_t}(T_j - T_t) + U.A. \frac{(T_j - T_t)}{V_t\rho_t Cp_t} \quad \ldots (6)$$

$$\frac{dT_j}{dt} = \frac{F_j}{V_j}(T_{ji} - T_j) - U.A. \frac{(T_j - T)}{V_j\rho_j Cp_j} \quad \ldots (7)$$

Thus the valve transfer function with a time delay of 1 second and a time constant of 3.8 seconds is expressed as,

$$H(S) = \frac{e^{-s}}{3.75s+1}Q(S) \quad \dots (8)$$

State-Space Model of CSTH

State Space model is the best method recommended to design and analyze a controller for a nonlinear multivariable process as mentioned in the literature with these forms, stirred tank heater model can also be used for direct multivariable regulator design and analysis. Both hot and cold water flows have linearized operational points. Table 2 shows the steady-state valve settings and instrument conditions. Variables reflect variations from the operational point in linearized models. At both the input and output, there are time delays.

By considering the above operating point, the state space linear model and transfer function model for Control Stirred Tank Heater are as follows from Eqs 9 to 22,

$$\frac{dx}{dt} = A\underline{x'} + B\underline{u'} \quad \dots (9)$$

$$\underline{y'} = C\underline{x} \quad \dots (10)$$

$$\begin{pmatrix} u_1'(t) \\ u_2'(t) \end{pmatrix} = \begin{pmatrix} u_1\ (t-1) \\ u_2\ (t) \end{pmatrix} \text{ And } \begin{pmatrix} y_1\ (t) \\ y_2\ (t) \\ y_3(t) \end{pmatrix} = \begin{pmatrix} y'_1\ (t) \\ y'_2\ (t) \\ y'_2(t-8) \end{pmatrix} \quad \dots (11)$$

$$G_{11}(\mathrm{s}) = \frac{4.5474*10^{-3}\ e^{-s}}{(s+3.931*\ 10^{-3})(s+2.732*\ 10^{-1})} \quad \dots (12)$$

$$G_{21}\ (\mathrm{s}) = \frac{1.6132*10^{-1}e^{-s}}{(s+2.732*\ 10^{-1})} \quad \dots (13)$$

$$G_{31}(\mathrm{s}) = \frac{-3.2422*10^{-3}e^{-9s}}{(s+2.932*10^{-2})(s+2.732*10^{-1})} \quad \dots (14)$$

Table 2 — Operating points for linearization

Variable	Operating point
Level (mA)	12.50
Level (cm)	20.55
CW flow (mA)	7.550
CW flow (LPH)	$3.823*10^{-5}$
Valve (mA)	11.50
Temperature (mA)	10.55
Temperature °C	42.55
Steam valve (mA)	6.553
HW flow(mA)	0
HW flow (LPH)	0

$$G_{32}(\mathrm{s}) = \frac{7.5867*10^{-2}e^{-8s}}{(s+2.932*10^{-2})} \quad \dots (15)$$

$$G_{13}(\mathrm{s}) = \frac{1.2540*10^{-2}e^{-8s}}{(s+3.931*10^{-3})} \quad \dots (16)$$

$$G_{33}(\mathrm{s}) = \frac{1.5867*10^{-2}e^{-8s}}{(s+2.932*10^{-2})} \quad \dots (17)$$

$$H\frac{dx}{dt} = A\underline{x} + B\underline{u'} \quad \dots (18)$$

$$\underline{y'} = C\underline{x}\begin{pmatrix} u'_1\ (t) \\ u'_2\ (t) \\ u'_3\ (t) \end{pmatrix} = \begin{pmatrix} u'_1\ (t-1) \\ u'_2\ (t) \\ u'_3\ (t) \end{pmatrix} \text{ and } \begin{pmatrix} y_1\ (t) \\ y_2\ (t) \\ y_3\ (t) \end{pmatrix} = \begin{pmatrix} y_1'(t) \\ y_2'(t) \\ y_3'(t) \end{pmatrix} \quad \dots (19)$$

The position of the cold water valve (u_1), the position of the steam valve, and Position of the hot water valve (u_3) are represented in the unit of mA. The level measurement (y_1), cold water flow measurement (y_2), and temperature measurement (y_2) are represented in the unit of mA. x_1 represents the volume of the tank and the integrator output, x_2 represents the output of the integrator in volume transfer function and x_3 represents the total enthalpy of tank and the output of enthalpy integrator.

$$A = \begin{pmatrix} -3.8313\times10^{-3} & 1.7789\times10^{-6} & 0 \\ 0 & -2.5316\times10^{-1} & 0 \\ 4.5580\times10^{3} & 3.7964\times10^{-1} & -2.9316\times10^{-2} \end{pmatrix} \quad \dots (20)$$

$$B = \begin{pmatrix} 0 & 0 & 4.3900\times10^{-5} \\ 1 & 0 & 0 \\ 0 & 6.5000\times10^{-1} & 8.9712 \end{pmatrix} \quad \dots (21)$$

$$C = \begin{pmatrix} 2790.0 & 0 & 0 \\ 0 & 1.6132\times10^{-1} & 0 \\ -1999.2 & 0 & 1.2226\times10^{-2} \end{pmatrix} \quad \dots (22)$$

Linearization of Transfer Function Model

In a closed-loop system, linearization of transfer function is required, as shown in Eqs 23 to 26. Because the level and temperature are monitored by the closed-loop control system, the input, and exit in this process cannot incorporate the time delay of CW valves and temperature gauges. In Fig. 4 depicts the linearised responses of CSTH's level, flow, and temperature control respectively.

$$G(s) = \begin{pmatrix} G_{11}(s) & G_{12}(s) \\ 0 & G_{22}(s) \end{pmatrix} \quad \dots (23)$$

$$G_{11}(s) = \frac{-0.29732(s-2)(s+0.0375)}{(s+2.034)(s+0.0580)(s^2+\ 0.1883s+0.01140)} \quad \dots (24)$$

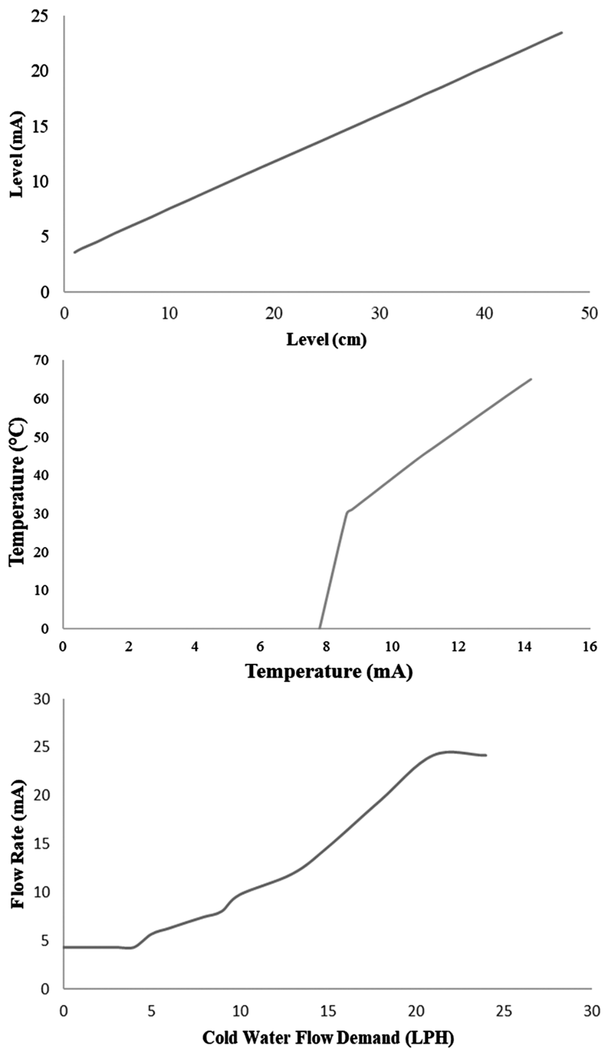

Fig. 4 — Linearised responses for controlling level, temperature, and flow in CSTH process

$$G_{12}(s) = \frac{0.013915s(s-2)(s-4)(s-0.2667)}{(s+3.931)(s+2.033)(s+0.05799)(s+0.04015)} \text{ x } \frac{-0.29732(s-2)(s+0.0375)}{(s^2+\ 0.1883s+0.01140)(s^2+\ 0.1761s+0.01892)} \quad \ldots (25)$$

$$G_{22}(s) = \frac{0.050561(s-4)(s-0.2667)(s+0.03333)}{(s+3.932)(s+0.04016)(s^2+\ 0.1883s+0.01140)} \quad \ldots (26)$$

Open-Loop Test

In an open-loop test, numerous steps are applied to varied step inputs to end control element. Pneumatic control valve is used as final control element to keep process's level and flow at the setpoint. The Silicon Control Relay is the last control device for controlling the temperature process (SCR). The process variable's dynamic behavior is observed. The test is repeated for various amounts of flow and temperature in CSTH for various set points by persistent disturbance. Input and output values are tabulated with regard to time, and graph is produced as shown in Fig. 5. As a result, neither the level nor the temperature is controlled at the stated points. It deviates from the predetermined goals.

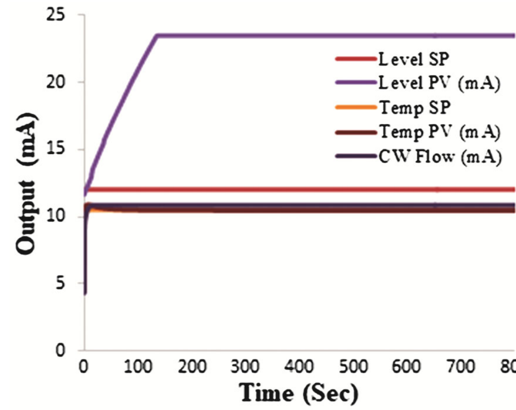

Fig. 5 — Response of open loop test

Controller Design

The PID controller is the utmost used feedback loop control algorithm. Many control engineers use such controllers in their daily work all over the world. The PID algorithm has the ability to view in several directions. It can be viewed as a gadget that can be controlled using a few rules, but it can also be analyzed as proposed by Trinh.[12]

PID Controller

Om Prakash and Gaurav[13] compare performance of PID, IMC, and Fuzzy logic controller to control boiler drum level. Among this setpoint, tracking is observed best for PID controllers. Thus the proportional, integral, and derivative modes are combined to perform powerful controller mode operations. As demonstrated in Fig. 6, this system can be employed for nearly any process situation.

The analytic expression is given in Eq. 27,

$$u(t) = Kp\ (e(t) + \frac{1}{T_i}\int_0^t e(t)dt + T_d \frac{de(t)}{dt}) \quad \ldots (27)$$

K_p is proportional gain between error and controller output

T_i is Integral time constant

T_d is derivative gain constant

$\frac{de(t)}{dt}$ is the rate of change of error

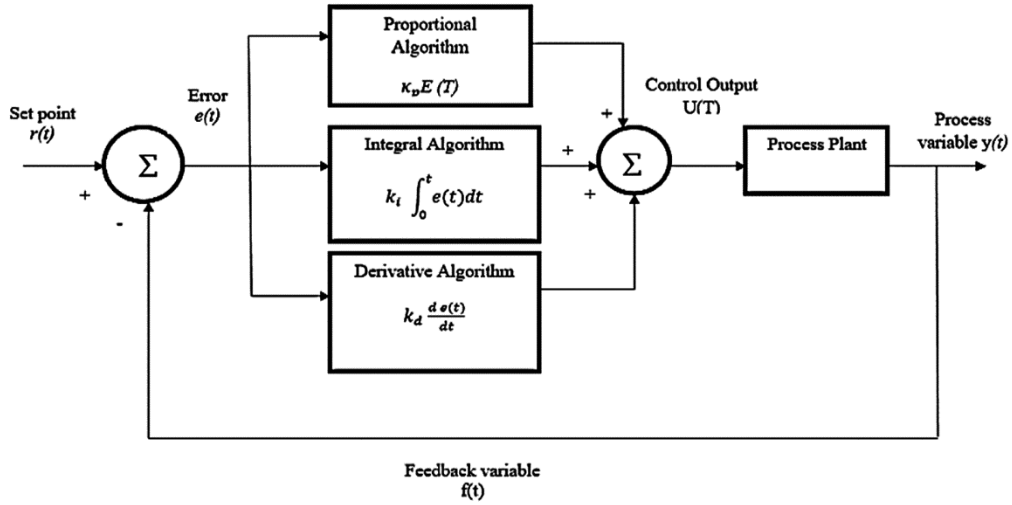

Fig. 6 — Block diagram of PID controller

Ziegler Nichols Tuning Technique

Ziegler Nichols Tuning Technique is a loop tuning technique based on trial and error that is still commonly used today. The technique for using the automatic mode (closed-loop) is as follows. Thus the Ziegler-Nichols tuning approach is used for a closed-loop operation because of its nature of extracting data in the open-loop response whereas process reaction curve method does not. Procedural step for this case is described below.

Step 1: When the process reaches the design level of operation, controller is set to P-Only mode and switched to automated.

Step 2: Kc is a guessed (assumed) initial controller gain that is good enough to keep the loop stable.

Step 3: The setpoint is slightly shifted, and the reaction behavior is monitored.

Step 4: The Kc is enhanced if the controller does not make the measured process variable (PV) sustain oscillations (or decrease the proportional band which is the PB).

Step 5: The Kc value is calculated using a trial-and-error process. The controller output (CO) should not be restricted, and these oscillations should neither expand nor die out.

Step 6: KU's ultimate gain is the controller gain in this circumstance. The ultimate period, PU, is the period of the PV oscillation pattern at the ultimate gain.

Step 7: Ziegler and Nichols advised the following settings for feedback controllers based on the KU and PU values, as shown in Table 3.

Table 3 — Tuning formula of ZN method

Controller Type	K_P	K_i	K_d
P	$0.5K_c$	0	0
PI	$0.45K_c$	$1.2K_PdT/P_c$	0
PID	$0.60K_c$	$2K_PdT/P_c$	$K_PP_C/ 8dT$

Optimization Techniques

An optimization algorithm is a large-scale technique that employs linear algebra without requiring the storage or operation of entire matrices Aditya and Vishnu.[14] This is accomplished internally by storing sparse matrices and computing with sparse linear algebra wherever possible. Wahid and Ghazali[15] describe the Optimum Design of the controller to increase stability.

The various optimization Techniques that are used for the selection of controller parameters are:

1. Genetic Algorithm,
2. F min Search,
3. Pattern Search,
4. Hybrid (Pattern Search + Fmin Search),
5. Hybrid (Genetic Algorithm + Pattern Search + Fmin Search).

This gives the proper fitness function for the controller to ratify the effectiveness of the process. The controller is being tuned accordingly by considering objective function of system such as Integral Square Error (ISE), Integral Absolute Error (IAE), and Integral Time Absolute Error (ITAE) by tuning gain factor K_p, K_i, and K_d as shown below detailed flow chart in Fig. 7. This is also being incorporated for the below optimization techniques to progress the accurateness and efficiency of the system

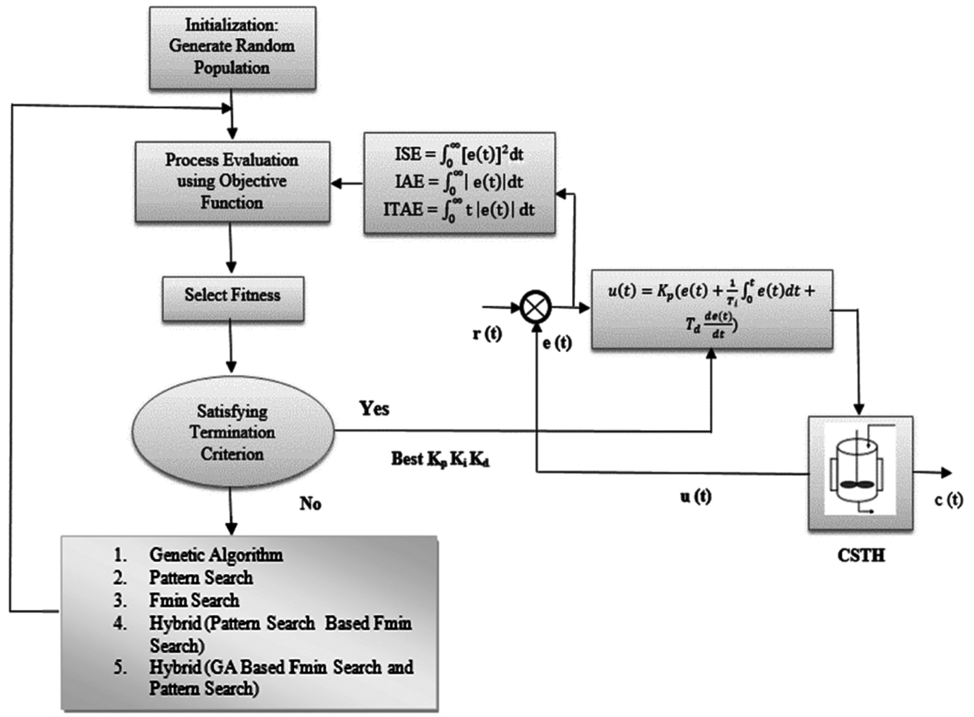

Fig. 7 — Flow diagram of optimization of CSTH process

by attaining the desired setpoint with an increase in a time domain specification. The below Eqs 28 to 30 describes the objective function,

Integral Square Error:

$$ISE = \int_0^\infty [e(t)]^2 dt \quad \ldots (28)$$

Integral Absolute Error:

$$IAE = \int_0^\infty | e(t)| dt \quad \ldots (29)$$

Integral Time Absolute Error:

$$ITAE = \int_0^\infty t\,|e(t)|\,dt \quad \ldots (30)$$

Genetic Algorithm

The genetic algorithm is used to iteratively alter the inhabitants of specific results. This ensures the effectiveness of the alogirthm parameters such as population size, Fitness Scaling Function, Crossover function, Crossover fraction, Migration fraction and Ending Migration are described in Table 4. The convergence rate of Genetic Algorithm is depends on these parameters for reaching the near global optimum. At each level, the genetic algorithm chooses parents arbitrarily from the existing population and customizes them to generate children for the succeeding generation. The population "evolves" to the best answer over time. The population's best point approaches an ideal solution. It chooses the next population by a computation that employs random number generators.

Table 4 — GA Parameters

Population type	Double vector
Population size	50
Fitness scaling function	Rank
Objective function	380
Crossver function	0.8
Crossover fraction	Scattered
Migration fraction	0.5
Ending criterion	150 iterations

Parameters used for tuning the PID controller by genetic algorithm are described in Eqs 31 to 33,

$$[Kp, Fv, eF, Op] = GA\ (ISE, Nvar, P1, Q1, Pequ1, Qequ1, Mb1, Hb1) \quad \ldots (31)$$

$$[Ki, Fv, eF, Op] = GA\ (ISE, Nvar, P2, Q2, Pequ2, Qequ2, Mb2, Hb2) \quad \ldots (32)$$

$$[Kd, Fv, eF, Op] = GA\ (ISE, Nvar, P3, Q3, Pequ3, Qequ3, Mb3, Hb3) \quad \ldots (33)$$

Nvar denotes variable numbers, P and Q indicates the constraint of linear inqueality matrix and vector. Pequ

& Qequ represents the constraints of linear equality matix and vector. Mb is to lower boundary value and Hb points the upper boundary value.

The reproduction function of the Genetic Algorithm is expressed in Eq. 34,

$$P_{ri} = \frac{F_i(\theta)}{\sum_{i=1}^{P_l} Fi(\theta)} \qquad \ldots (34)$$

where, P_{ri} is the reproduction function

$F_i(\theta)$ – Fitness function

The fitness function represents objective function which required for minimizing. Fitness function's number of independent variables is specified by count of variables. Range of independent variables in the fitness function is determined by the lower and upper bounds, which set minimum and maximum values for the variables as defined within the constraints. The term "Population" indicates the selection of the population size for genetic algorithm. The term "Population type" designates nature of the feed supplied to the fitness function. The fittest chromosome is assigned, which results in a superior system response. Let the lower and upper boundary limits of proportional gain (gene1) and integral time (gene2) for level, Temperature and flow be Level = {Kp: 2, Ki: 0.1}, Temperature = {Kp: 3, Ki: 0.1} and Flow = {Kp: 0.5, Ki: 0.2}. Where upper bound be given as Level = {Kp: 3.5, Ki: 0.5}, Temperature = {Kp: 4, Ki: 0.2} and Flow = {Kp: 1.0, Ki: 0.5} respectively.

↓ ↓ x y

Let the Selected gain = x Modified gain = x-0.20 If (Modified gain < 12.0) then Modified gain =x+0.2 (Child) Level = {Kp: 3, Ki: 0.2}, Temperature = {Kp: 3.9, Ki: 0.19} and Flow = {Kp: 0.6, Ki: 0.3} by considering objective functions.

Pattern Search Algorithm

The pattern search algorithms generate a series of points that eventually converge on an ideal point. The program checks each step's mesh of points surrounding the current position. To generate the mesh, a scalar multiple of a pattern, which is a vector collection, is multiplied by the current point and identifies the spot in the current network. Fitness function estimates the tracking of nearest value of objective function in this approach, for example, considers a poll to be unsuccessful if all points are evaluated to NaN, shrinks the mesh, and revalues. The parameters for optimizing the process through the pattern search Algorithm are specified in Table 5. Convergence of this algorithm implies the improvement of objective function and iteration stops when the defined criteria is satisfied.

Table 5 — PS parameters

Poll method	GPS positive basis 2N
Initial point	1.0
Step size	2.0
Mesh size	Infinity
Maximum iteration	100
Convergence tolerance	0.1
Objective function	380

The lower point and upper boundary values that have been considered are, Level = {Kp: 0.5, Ki: 0.1}, Temperature = {Kp: 0.1, Ki: 0.1}, and Flow = {Kp: 2.5, Ki: 0.1}. Where upper bound be given as Level = {Kp: 2.5, Ki: 0.5}, Temperature = {Kp: 1.0, Ki: 0.5} and Flow = {Kp: 3.5, Ki: 0.5}. The spot identified in the network as the final value for optimizing the process as the gain factor by pattern search is obtained as, Level = {Kp: 2, Ki: 0.1}, Temperature = {Kp: 0.5, Ki: 0.2} and Flow = {Kp: 3, Ki: 0.1} with an objective function.

Fmin Search Algorithm

Fmin search determines the smallest scalar function of many variables by departing with initial estimate. This is commonly known as unconstrained nonlinear optimization. The convergence of this approach narrows down the search space instead wider to reach local optimum more efficiency. The algorithm iterates multiple times until it obtains the optimal fit values. In the event of an identified issue, the algorithm terminates, and the termination reason is displayed.

Whereas Z = fmin search (fun Z0) begins at x0 and returns a result x is a particular minimizer of the function represented by fun. z0 can be either a scalar, a vector, or a matrix. The word "fun" is a function handle. Z = fmin search (fun, z0, options) minimizes using the structure options' optimization parameters. The function to be minimized is fun. It takes an z as an input and returns a scalar f, the objective function evaluated at Z. The minimal value is determined as Z = (Z1, Z2, Z3) by considering the objective function. Fitness function takes array of parameters as input and computes objective function based on it.

$$[Kp, fivalue1, exflag1, out1, La, Gra, He] = f\,(ISE, Z1, p1, q1, Peq1, qeq1, lowb1, upbound1, W1, V1) \quad \ldots(35)$$

$$[Kp, fivalue2, exflag2, out2, La, Gra, He] =$$

$$f\ (ISE, Z2, p2, q2, Peq2, qeq2, lowb2, upbound2, W2, V2) \quad \ldots (36)$$

$$[Kp, fivalue3, exflag3, out3, La, Gra, He] = f\ (ISE, Z3, p3, q3, Peq3, qeq3, lowb3, upbound3, W3, V3) \quad \ldots (37)$$

Algorithm commences with an initial value and proceeds to determine minimum value of function, primarily based on the objective function ISE as shown in Eqs 35 to 37. In MATLAB, we use the following abbreviations:"fmincon" is represented as "f", "fivalue" represents final value, "exflag" for exit flag, "out" referred for the output value , Lagrange multipliers is represented as “La” , PID parameters objective function is indicated as “ Gra”, Linear inequality function of vector and matrix is represented by "q" and "p", Matrix and vector linear equality constraints are referred as "peq" and "qeq”, Mininum bounded value is indicated as “lowb”, while maximum boundary is represented as “upbound”, "fivalue" denotes the final objective function, Hessian parameter objective function is indicated as "H", "O" designates the option that yields a grasping of information pertaining to the optimization solution.

Fmin search employs the simplex search method. The lower point and upper boundary values that have been considered are, Level = {Kp: 6.0, Ki: 0.15}, Temperature = {Kp: 0.2, Ki: 0.2}, and Flow = {Kp: 3.0, Ki: 0.1}. Where higher bound value be given as Level = {Kp: 7.0, Ki: 0.2}, Temperature = {Kp: 3.5, Ki: 0.5} and Flow = {Kp: 0.5, Ki: 0.5}. The final gain value is obtained as, Level = {Kp: 6.5, Ki: 0.15}, Temperature = {Kp: 3.36, Ki: 0.21} and Flow = {Kp: 0.33, Ki: 0.38} based on objective functions IAE, ISE, and ITAE.

Hybrid Optimization Algorithm

Hybridization is the integration of two or more optimization algorithms that work together to tune the controller's gain factors and determine the process's stability in an efficient manner. Arunjayakar and Senthil Kumar[16] proposed the importance of a hybrid algorithm for highly non-linear processes. Sakthiyaram and Kumar[17] describe the stability analysis of the controller designed for non-linear processes using a hybrid optimization algorithm. For analysis, the following hybrid optimization strategies were used.

1 Pattern + fmin search algorithm
2 GA + pattern search + fmin search algorithm

Hybrid Pattern + Fmin Search Algorithm

The novel technique presented in this study is a hybrid pattern search-based Fmin algorithm to tune the gain factors of the PID Controller whereas variables tuned by pattern search for level, temperature, and flow are cascaded with the Fmin search to get fine-tuned gain values for further analysis. Hybridizing these techniques will result in faster convergence to a local optimum and enable effective handling of constraints and more complex objective functions.

GA-Based Pattern Search + Fmin Search Algorithm

The unique approach demonstrates the hybridization of the Genetic algorithm, Pattern Search, and Fmin search optimization algorithms to examine system performance by modifying the gain factors KP, Ki, and Kd of level, flow, and temperature controllers. In this approach, the GA generates a wide range of parameter combinations within a population based on the fitness function. It then selects the best individual and passes it to Pattern Search, which effectively identifies the best local optima for each individual. When Fmin Search is applied, it further refines the solution by fine-tuning the parameters using gradient information.

Results and Discussion

The simulation and real-time response of process is compared and validated in this section. In Figs 8, 9, and 10 the comparison and validation of the response obtained from the simulated and real-time model for controlling the level, Temperature, and Flow of CSTH using various optimization techniques respectively have been given. It is discovered that the hybrid (GA+Fmin+Pattern Search) optimization outperforms

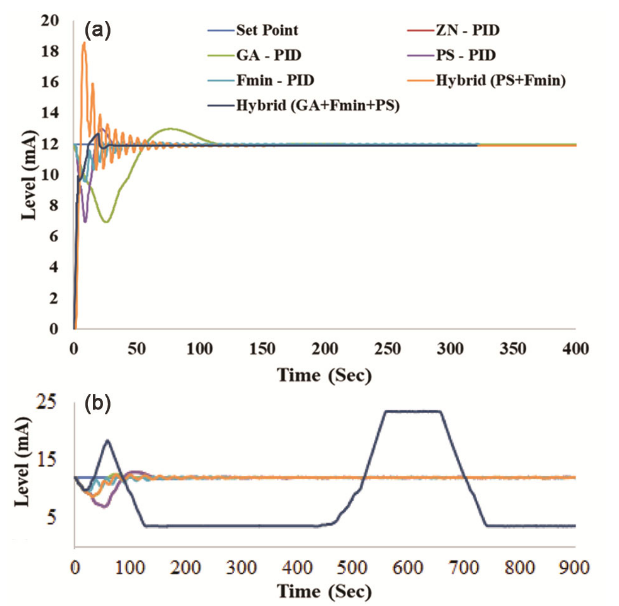

Fig. 8 — Comparison and validation of controlling the Level of CSTH process using various optimization techniques: (a) Simulation and (b) Experimental responses

other optimizations such as Ziegler Nicholas PID, Genetic Algorithm, Fmin Search, Pattern Search, and Hybrid (Pattern Search + Fmin Search). It is clear that when hybrid (GA+Fmin+Pattern Search) optimization techniques for controller tuning are used, the process output of the controlling level and Temperature of CSTH responds quickly. In Table 6 a comparison of time-domain specifications for level and temperature in CSTH using various tuning techniques for both experimental and theoretical approaches is displayed. Finally, it is inferred that the model response obtained in both simulations and in real-time coincides with an approximation of about 90 percent. The controller parameters of various controllers used for controlling the level, Flow, and Temperature of CSTH in the proposed work re given in Table 7.

The performance of each optimization technique for controlling the level and temperature is strongly clarified in Table 4 by describing the time domain specifications. Based on its controller action, the hybrid (GA+PS+Fmin) has a minimum rise time of about 21.25 sec, a settling time of about 66.25 sec, and a peak time of about 20.25 sec. Similarly, when focusing on the temperature control parameters, it is clear that the implemented Hybrid algorithm has rise times, settling times, and peak times of approximately 15 seconds, 25.00 seconds, and 20.25 seconds, respectively. As a result, Hybrid optimization techniques are preferable for controlling the level and

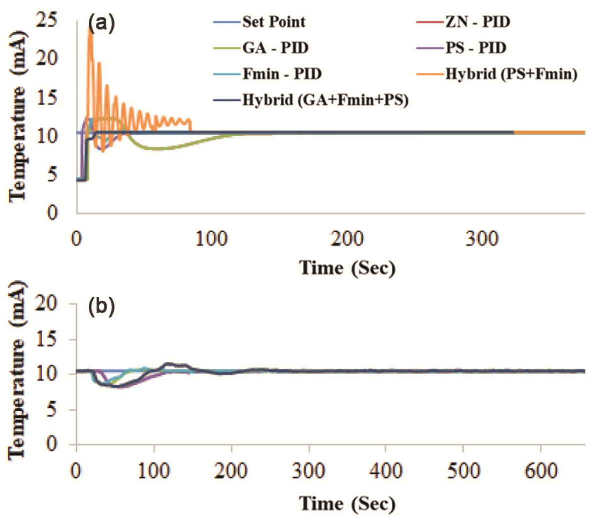

Fig. 9 — Comparison and validation of controlling the Temperature of the CSTH process using various optimization techniques: (a) Simulation and (b) Experimental responses

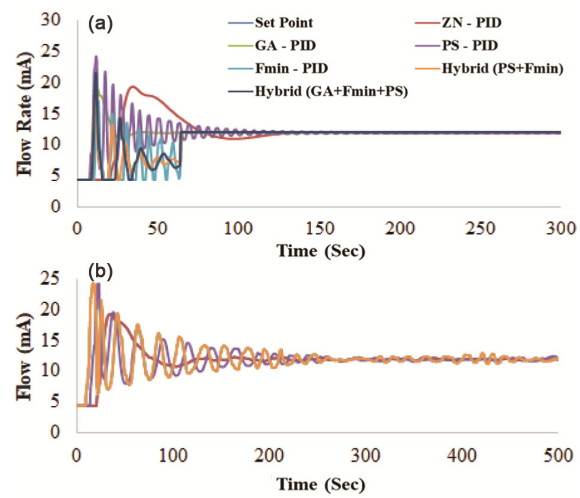

Fig. 10 — Comparison and validation of controlling the Flow of the CSTH process using various optimization techniques: (a) Simulation and (b) Experimental responses

Table 6 — Time domain specification of different optimization techniques for liquid level and temperature control obtained in simulation and experimental approach

Process variables	Optimization techniques	Time domain specifications in simulation			Time domain specifications in experimentation		
		Rise time (Sec)	Settling time (Sec)	Peak time (Sec)	Rise time (Sec)	Settling time (Sec)	Peak time (Sec)
Level	ZN PID	57.50	79.50	77.75	77.50	99.50	87.75
	GA PID	55.75	68.75	75.50	65.75	68.75	85.50
	Pattern search Method	45.50	95.50	22.75	45.50	95.50	22.75
	Fmin search	34.50	90.50	28.25	34.50	90.50	28.25
	Hybrid (PS + Fmin)	40.25	85.25	20.50	40.25	85.25	20.50
	Hybrid (GA+ PS + Fmin)	**21.25**	**66.25**	**20.25**	**21.25**	**66.25**	**20.25**
Temperature	ZN PID	23.25	51.00	28.25	23.25	51.00	28.25
	GA PID	50.25	42.00	25.50	50.25	42.00	25.50
	Pattern search method	59.25	63.75	10.25	59.25	63.75	10.25
	Fmin search	36.25	100.25	12.25	36.25	100.25	12.25
	Hybrid (PS + Fmin)	35.75	84.00	29.00	35.75	84.00	29.00
	Hybrid (GA+ PS + Fmin)	**15.00**	**25.00**	**20.25**	**15.00**	**25.00**	**20.25**

Table 7 — Control parameters for controlling level, flow, and temperature using various controllers

Parameters	Level		Flow		Temperature	
	Kp	Ki	Kp	Ki	Kp	Ki
ZN PID	2.0	0.1	0.5	0.2	3.0	0.1
GA PID	3.0	0.2	0.6	0.3	3.9	0.19
Pattern search method	2.2	0.15	0.7	0.5	3.2	0.2
Fmin search	6.5	0.15	0.33	0.38	3.36	0.21
Hybrid (PS + Fmin)	3.5	0.16	0.001	0.31	1.2	0.14
Hybrid (GA+ PS + Fmin)	**2.9**	**0.3**	**0.23**	**0.28**	**1.36**	**0.19**

Table 8 — Comparison of integrated error performance indices in simulation and experimentation using different optimization techniques

Parameters	Optimization techniques	Performance indices in simulation			Performance indices in experimentation		
		ISE	IAE	ITAE	ISE	IAE	ITAE
Level	ZN PID	512.53	200.72	981.43	551	231	980
	GA PID	383.66	127.25	980.83	103.11	136.51	996.77
	Pattern Search Method	512.53	200.72	981.43	520.55	210.15	990.23
	Fmin Search	537.73	674.06	975.87	600.44	700.15	993.25
	Hybrid (PS + Fmin)	391.23	169.95	953.11	175.27	155.44	997.30
	Hybrid (GA+ PS + Fmin)	**110.39**	**114.50**	**950.86**	**101.40**	**130.47**	**900.15**
Temperature	ZN PID	200.12	174.11	945.01	207.22	184.21	978.01
	GA PID	94.43	112.23	913.53	103.45	132.23	979.33
	Pattern Search Method	95..27	110.87	975.89	99.27	136.90	975.99
	Fmin Search	99.17	128.90	935.99	98.27	136.90	975.99
	Hybrid (PS + Fmin)	107	214	954.50	127	224	994.50
	Hybrid (GA+ PS + Fmin)	**90.17**	**106.87**	**900.75**	**92.27**	**130.60**	**899.17**

temperature of the CSTH process. Comparision of the Integrated Error ISE, IAE, and ITAE of various optimization techniques to describe the error performance criteria for simulation and real-time approach are given in Table 8.

The performance is generated in different optimization techniques. The Integrated Square Error for ZN PID, GA PID, Pattern Search method, Fmin Search, Hybrid (PS+ Fmin), and Hybrid (GA+PS+Fmin) is 512.53, 383.66, 512.53, 537.73, 291.23 and 110.39 respectively. In addition, the IAE generated by each technique is 200.72, 127.85, 200.72, 674.06, 169.95 and 114.50. The ITAE incorporated when using Hybrid (GA+PS+Fmin) is 950.86, which is lower than that of other advanced techniques. Thus the response of the CSTH is well settled in the required setpoint while Hybrid (GA+PS+Fmin) Algorithm is compared to other optimization techniques in both simulation and experimental approaches.

Conclusions

The energy balance ensures that the tank operates under the right conditions by accounting for parameters such as maintaining the desired temperature and controlling process kinetics. On the other hand, the mass balance is crucial for maintaining the process's flow rates by controlling the inflow and outflow of reactants to ensure process safety. The proposed optimization methods provide precise models for controlling level and temperature of CSTH process station in both real-time and simulation approaches. Both models have been validated by necessary techniques. When compared to Ziegler-Nichols (Z-N) tuning techniques, the hybrid fmin search – Pattern Search and hybrid Genetic Algorithm – Pattern Search – Fmin Search based transfer function models provide proper dynamic behavior, and proposed controller optimization techniques generate the optimum values of the PID controller with smallest error values of IAE, ISE, and ITAE for immeasurable disturbance and setpoint variations. PID controller based on Genetic Algorithm provides a closed response with no peak overshoot but a long settling time. Fmin Search – Pattern Search – Genetic Algorithm hybrid PID controllers outperform other PID controllers in positions of low overshoot and settling time (t_s), so they are recommended for CSTH process. It provides a very good solution to industrialists in terms of reducing manpower and improving energy efficiency and indirectly in economic aspects.

Sensor and actuator faults in CSTH process are considered in the future for analysis and diagnosis.

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