SYSTEM IDENTIFICATION OF BATCH VACUUM PAN FOR SIMULATION

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Abstract— **In this paper, black box system identification and modeling of batch vacuum PAN are proposed. System identification is a technique by which system can be represented in mathematical terms from observed input-output data. The system identification can be used for any system and can be termed into the mathematical equation for computer simulation. With a mathematical model output of a system can be predicted for given known input. This paper discusses modeling of vacuum batch PAN system of sugar processing plant. Data captured from field devices are firstly analyzed to find the relationship of parameters against output and then directly expressed using mathematical autoregressive equation. This model is used to build a control system for PAN.**

Index terms: - MODELLING, SIMULATION, REGRESSION ANALYSIS, SCATTER PLOT, PID.

I. INTRODUCTION

The batch vacuum PAN is the main part of sugar boiling process [1]. Building model is a good way to develop control system. Once the control system is developed it can be deployed in the real application. This reduces the development cost and time. To build a PAN model the behavior of the current system is logged. The relation between input and output data is visualized using scatter plot. This logged input-output data is then analyzed and the relation between them is expressed in the mathematical term. This mathematical model is then used for simulation of PAN system [1] [2] [3] [4] [5].

The system identification is a technique by which system can be represented in mathematical terms from observed input-output data. The system identification can be used for any system and can be termed into the mathematical equation for computer simulation. With a mathematical model output of a system can be predicted for given known input. The system is known to be linear if it follows superposition principle else it is non-linear [6]-[12]. i.e. If system respond for zero input with zero output, then it is called linear satisfying

$$x_1(t) = y_1(t) \text{ and for } ax_1(t) + bx_1(t) = ay_1(t) + by_1(t) \tag{1}$$

where a, b is system constant.

- **WHITE BOX IDENTIFICATION**:

White box modeling of a physical system can be done using the first principle referred to as postulates and axioms. If system parameters are known, it can be expressed directly in the equation. Development of mathematical model from an understanding of physical laws is very much complex and even sometimes impossible for many industrial systems. Testing of such system can be done if and only if the systems internal working is known.

- **GRAY BOX IDENTIFICATION:**

Gray box modeling is a technique, where the system is partially known (theoretical structure) and partially derived from the system data. Models theoretical structure must be evaluated individually. For a particular model structure parameter, can be found using the direct relation between input-output relation. Grey box modeling works for a system where some parameters of the system are known.

- **BLACK BOX IDENTIFICATION:**

Black box modeling of a system is convenient if the theoretical knowledge of the system is unknown. System modeling is done in this case by analyzing input-output of data. The advantage of this technique is system can be modeled without knowing the internal working of the system. Implementation is completely opaque and referred to only systems behavior. Application of black box system identification includes process control application, aeronautics, biological systems, medicines [13]-[20].

II. REGRESSION AND DATA ANALYSIS

Polynomial regression is the method of obtaining of approximate polynomial function from input-output data points. When data read from sensors it is with inaccuracies and non-linearity. Linearity is a naturally existing phenomenon. All physical systems are weakly non-linear. This system identification technique is useful when modeling not able to capture system dynamics. Table 1 shows reading obtained from sensors of the batch vacuum PAN for different boiling phases.

Table 1: Reading obtained from sensors of PAN floor

Sample No	Temperature	Level	Vacuum	Brix
1.Drwaing in	38	0	14.70	0
2.Drwaing in	40.20	12.50	14.51	38.30
3.Drwaing in	40.50	22.47	13.65	38.95
4. Concentration	41.20	30.00	13.17	38.80
5.Concentration	41.50	32.44	12.86	40.65
6. Seeding	42.90	35.60	12.81	52.28
7. Seeding	43.65	35.62	12.70	60.13
8. Graining	46.41	46.36	12.65	62.65
9. Graining	55.78	52.80	12.50	62.20
10. Graining	55.35	69.40	12.44	68.15
11. Boiling	56.71	72.18	12.43	73.56
12. Boiling	56.12	70.39	12.50	74.65
13. Boiling	61.31	73.50	12.65	76.51
14. Brixing Up	62.25	70.84	12.50	78.95
15. Brixing Up	65.75	70.14	12.65	81.70
16. Brixing Up	64.45	70.56	12.40	83.20
17. Brixing Up	64.65	70.68	12.43	85.65
18. Discharge	64.48	70.69	13.58	88.23
19. Discharge	64.31	60.78	14.27	88.25
20. Discharge	40.2	0	14.70	0

The fig 1 to fig 3 shows scatter plot for a system with input-output data. The scatter plot for Brix against system Temperature is non-linear, Brix against system Level is linear and Brix against system Vacuum shows non-linearity. Brix against system temperature is nonlinear rather its exponential in nature. Level and brix linear at a range of 30º C to 80º C but there isn't any relation with a vacuum.

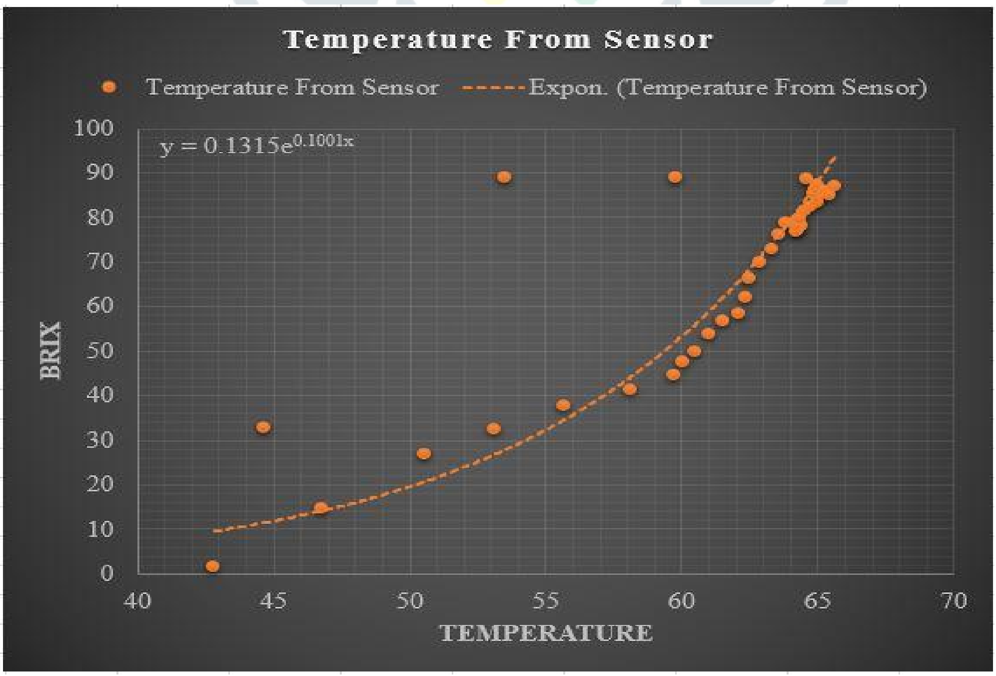

Fig. 1: Scatter Plot-Temperature vs Brix

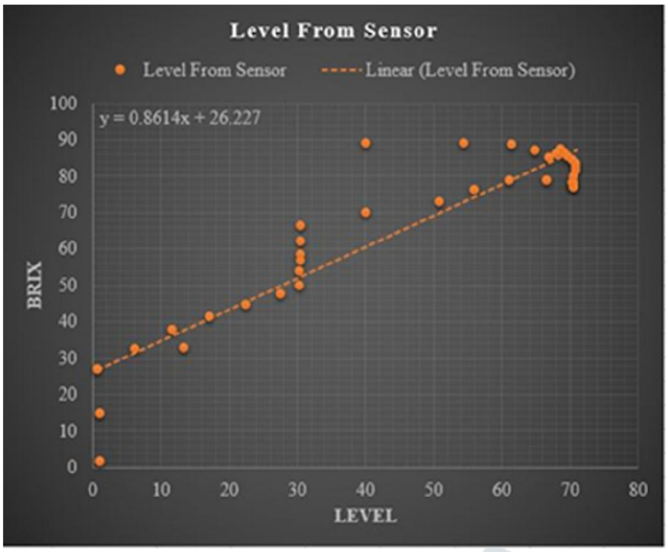

Fig. 2: Scatter Plot-Level vs Brix

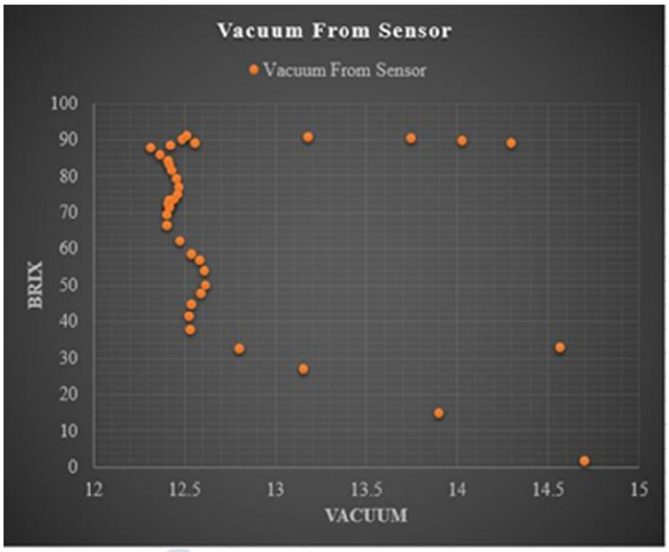

Fig. 3: Scatter Plot-Vacuum vs Brix

The regression equation for the linear system can be represented by.

$$y = a_0 + a_1 x \quad (1)$$

$$a_0 = \frac{(\sum y)(\sum x^2) - (\sum xy)(\sum x)}{n(\sum x^2) - (\sum x)^2} \quad (2)$$

$$a_1 = \frac{n(\sum xy) - (\sum y)(\sum x)}{n(\sum x^2) - (\sum x)^2} \quad (3)$$

n is sample number. This black box modeling technique uses linear regression to estimate the linear model, this estimated model is nothing but approximated mimic of the system. But the problem with this estimation method is system cannot be expressed correctly with delayed output, i.e. when any input is applied system not reacts quickly so prediction using this formula won't work. For such case estimation, can be done using art model with delayed input.

Design of brix model for simulation

The general form of relationship between input and output signal is given as follows.

$$y(t) = f(u(t-1), y(t-1), u(t-2), y(t-2), \ldots) \quad (4)$$

Where y(t) is output u(t) input relates each other with some function. Identification of dynamic system can be done with the least square method. The transfer function for the discrete-time dynamic system is estimated with autoregressive exogenous (ARX) modeling, which gives the transfer function in the z-domain [18]-[22].

$$\begin{aligned} &y_n + a_1 y_{n-1} + a_2 y_{n-2} + a_3 y_{n-3} + .. a_n y_{n-N} = \\ &b_0 {}^1x_n + b_1 {}^1x_{n-1} + b_2 {}^1x_{n-2} + b_3 {}^1x_{n-2} + .. b_n {}^1x_{n-N} + \\ &c_0 {}^2x_n + c_1 {}^2x_{n-1} + c_2 {}^2x_{n-2} + c_3 {}^2x_{n-2} + .. c_n {}^2x_{n-N} + e_k .. \end{aligned} \quad (5)$$

The dynamical system can be represented by difference equation

$\because {}^1x$, ${}^2x$ are systems two different input, e is the error term, a, b, are the parameters of the system to be estimated.

e_k the error caused by the measurement.

$$\sum_{k=0}^{N} a_k y_{n-k} = \sum_{k=0}^{N} b_k {}^1x_{n-k} + \sum_{k=0}^{N} c_k {}^2x_{n-k} + e_k$$

$$y_n = \frac{\sum_{k=0}^{N} b_k {}^1x_{n-k}}{\sum_{k=1}^{N} a_k y_{n-k}} + \frac{\sum_{k=0}^{N} c_k {}^2x_{n-k}}{\sum_{k=1}^{N} a_k y_{n-k}} + \frac{e_k}{\sum_{k=1}^{N} a_k y_{n-k}} \quad (6)$$

This equation in terms of z-transform can be written as

$$y_n = \frac{B_k}{A_k}{}^1x + \frac{C_k}{A_k}{}^2x + \frac{1}{A_k}e_k \quad (7)$$

$$A_k = 1 - a_1z^{-1} + a_2z^{-2} + a_3z^{-3} + ... + a_nz^{-n}.)$$
$$B_k = b_1z^{-1} + b_2z^{-2} + b_3z^{-3} + ... + b_nz^{-n}.$$
$$C_k = c_1z^{-1} + c_2z^{-2} + c_3z^{-3} + ... + c_nz^{-n} \quad (8)$$

z^{-1} is z-transform in time shift operator. $z^{-1}V(t) = V(t-1)$

Determination of coefficient can be done using the least square method. Let order of the system be 2 then in matrix form it can be represented by

$$\underbrace{\begin{bmatrix} y_3 \\ y_4 \\ \vdots \\ y_n \end{bmatrix}}_{Y} = \underbrace{\begin{bmatrix} y_2 & y_1 & {}^1x_1 & {}^2x_1 \\ y_3 & y_2 & {}^1x_2 & {}^2x_1 \\ \vdots & \vdots & \vdots & \vdots \\ y_{n-1} & y_{n-2} & {}^1x_n & {}^2x_n \end{bmatrix}}_{\Omega} * \underbrace{\begin{bmatrix} a_1 \\ a_2 \\ b_1 \\ b_2 \end{bmatrix}}_{\theta} + \underbrace{\begin{bmatrix} e_3 \\ e_4 \\ \vdots \\ e_n \end{bmatrix}}_{e}. \quad (9)$$

Writing above equation in vector form.

$$Y = \Omega\theta + e$$

$$\hat{\theta} = \min_{(a_1,a_2,b_1,b_2)} \sum_{k=2}^{N} [e_k]^2 = \sum_{\theta}^{\min} e^T e. \quad (10)$$

The smallest value (minima) of the sum of squares can be calculated by setting the gradient to zero.

$$\Psi = e^T e = [Y - \Omega\theta]^T [Y - \Omega\theta] \quad (11)$$

Least square of θ_{ls} is

$$\frac{\partial \Psi}{\partial \theta} = \left[\frac{\partial \Psi}{\partial a_1} \frac{\partial \Psi}{\partial a_2} \frac{\partial \Psi}{\partial b_1} \frac{\partial \Psi}{\partial b_2} \right]^T = 0$$
$$\frac{\partial \Psi}{\partial \theta} = \frac{\partial [Y - \Omega\theta]^T [Y - \Omega\theta]}{\partial \theta}.$$
$$\frac{\partial \Psi}{\partial \theta} = \Omega^T [Y - \Omega\theta] = 0$$
$$\theta_{ls} = \left[\Omega^T * \Omega \right]^{-1} * \Omega^T Y \quad (12)$$

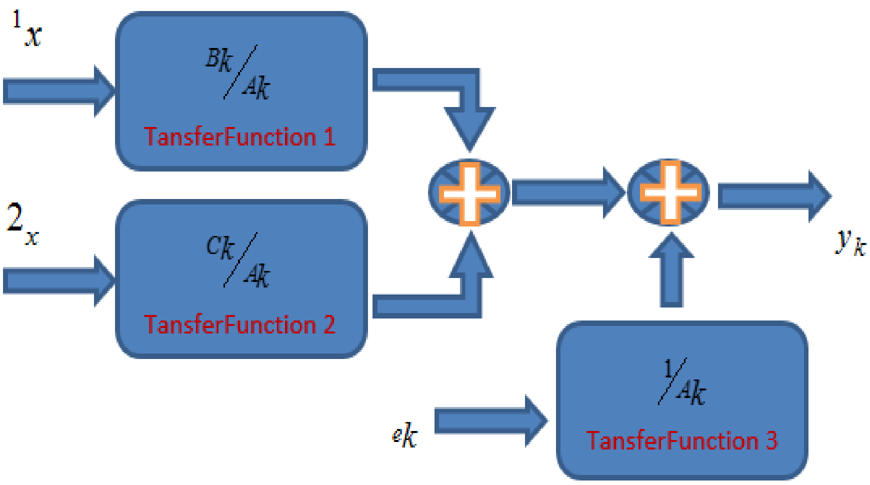

Fig. 4: Transfer function representation of Brix model

Transfer function obtained from collected data is

$$
\begin{aligned}
A_k &= 1 - 1.843\, z^{-1} + 3.531\, z^{-2} - 3.274\, z^{-3} + 1.807\, z^{-4} - 1.048\, z^{-5} \\
B_k &= 5.222\, z^{-1} - 4.908\, z^{-2} \\
C_k &= -0.4049\, z^{-1} + 0.3608\, z^{-2}
\end{aligned} \tag{13}
$$

III. Model Simulation

The model developed using the ARX technic is shown fig 5 used for simulation. Simulation result for developed brix model matches 93% to the original system. The 7% inaccuracy in the model is because of the reading errors, sensor dynamics. The fig.6 shows the actual output of system and output of estimated model. This model is used for PID simulation and obtaining brix value at different set points of PAN parameters like temperature pressure and vacuum.

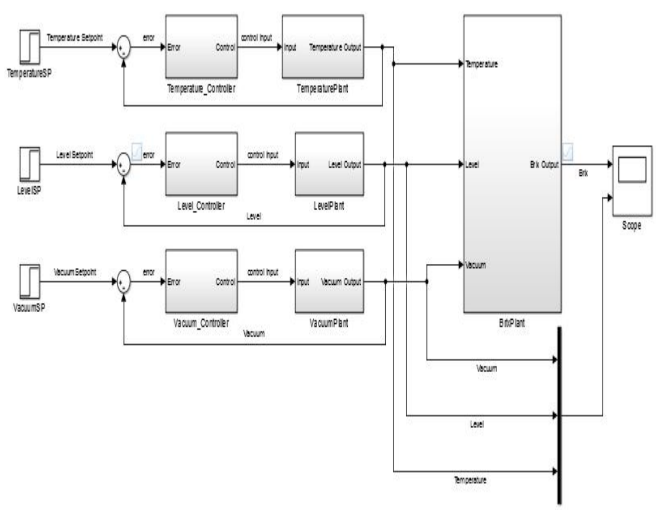

Fig. 5: Brix Simulation plant model.

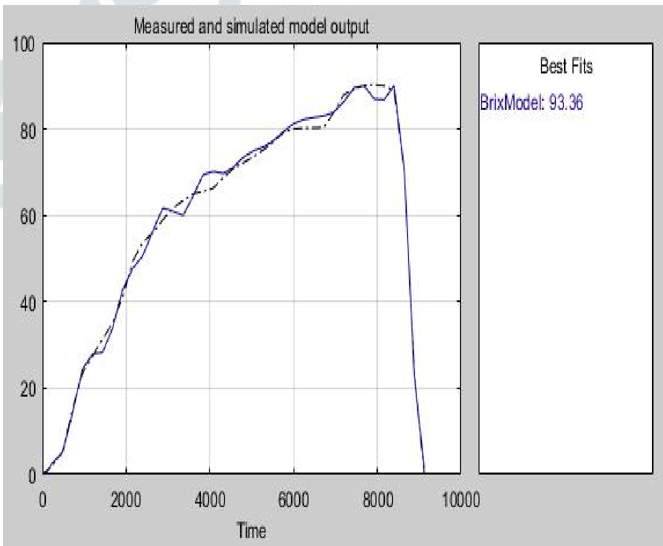

Fig 6: Comparison actual and estimated Brix model output

IV. Result and Discussion

PID SIMULATION:

The PAN control system is designed with the state-based approach and PID control for parameters are achieved. PID simulation results for various parameters like Temperature, Vacuum and Level and its impact on brix are shown in fig 7 to fig 10. PID simulation result of approximated brix model shows nearly 93% accuracy to the actual system. The control system in process industry for brix monitoring is a complex nonlinear, the direct PID control is limited to a linear system, so the control consequence is not perfect. Dividing the process in the state makes the system piecewise linear and controlling of the system with PID control within state gives best results.

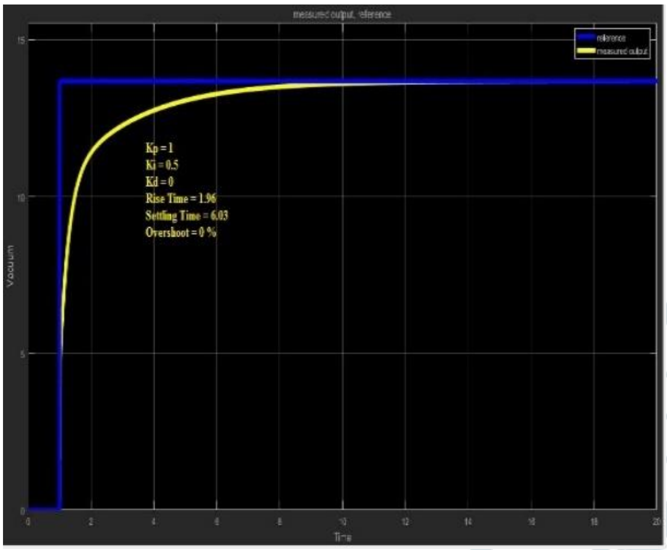

Fig 7: PID simulation for vacuum

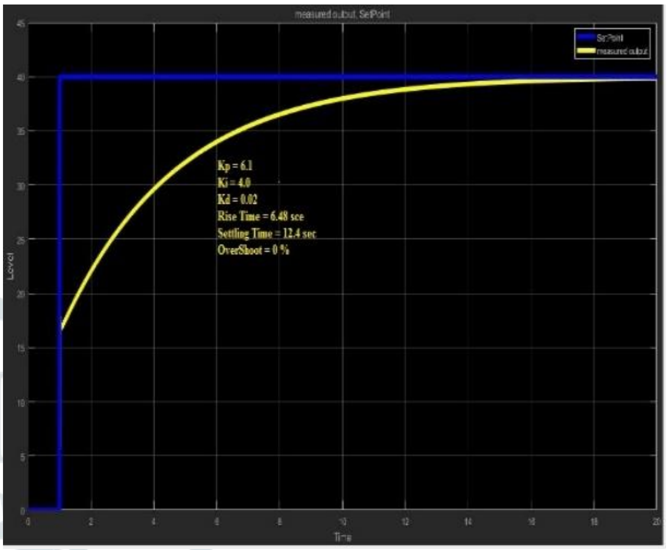

Fig. 8: PID simulation for level

Fig. 7 shows a PID simulation of Vacuum profile. With kp =1, ki = 0.5, kd = 0 and settling time= 6.03 sec. Fig 8 shows a PID simulation of the Level profile. With kp =6.1, ki = 4.0, kd = 0.02 and settling time= 12.4 sec.

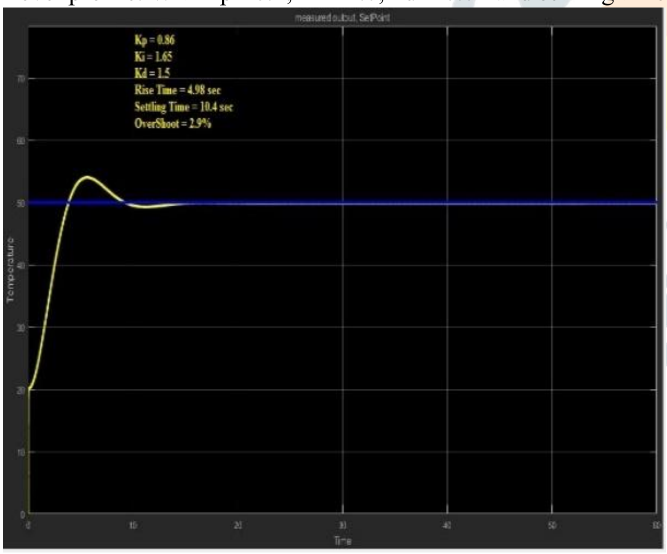

Fig. 9: PID simulation for temperature

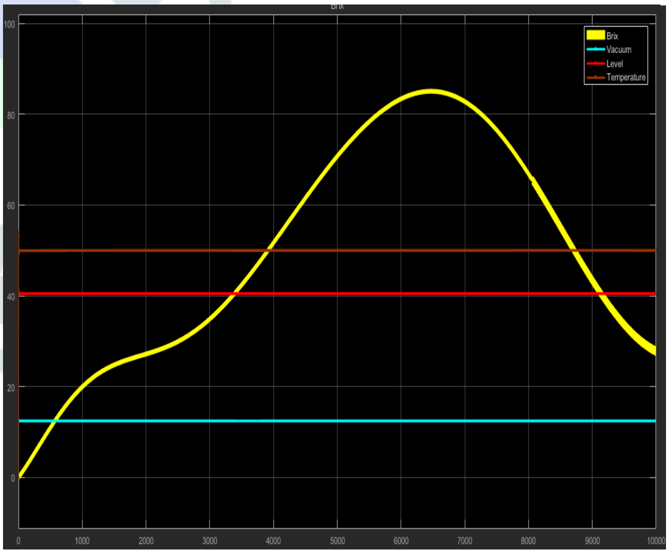

Fig. 10: Brix model simulation output

Fig.9 shows PID simulation of the Temperature profile. With kp =0.86, ki = 1.65, kd = 1.5 and settling time= 10.4 sec. This is the settling time for the single state of PAN control system. Fig 10 shows a PID simulation of brix profile. These simulations are done for single PAN boiling process state.

In this paper, we have proposed black box system identification of vacuum batch PAN. This model is used for making control system more effective. This vacuum batch PAN automation will certainly bring effectiveness besides easiness for the operator on PAN floor which will permit the sugar industry to mark max profit at lowest charge. Few of the benefits that will be observed after the execution are as follows

V. CONCLUSION.

By using brix model the batch vacuum PAN can be automated for good result. The system can bring the good results. Simulation brings downs the control system development time and cost. For various input systems behavior can be predicted, this leads to improvement in the development of PAN control system. Precaution limits can be tested with this developed model.

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