Parameter Estimation of a Multiple-Effect Evaporator by Genetic Algorithms

Arvin V. Pitteea, Robert T. F. Ah King and Harry. C. S. Rughooputh
Department of Electrical and Electronic Engineering
Faculty of Engineering
University of Mauritius
Reduit, Mauritius
r.ahking@uom.ac.mu

Abstract – **This paper proposes a hybrid approach to the modelling of actual plants. Genetic Algorithms are used to estimate and tune some of the physical parameters and, if required some variables also, of a mathematical model of a process to obtain the required outputs. The approach has been verified on a Multiple-Effect Evaporator (MEE) in the sugar industry. The results confirm the potential of the technique, which may be applied in situation where fairly accurate mathematical models are available but are not predicting the outputs as evidenced in practice. If some accurate plant data are available, the approach presented in this paper can be used to optimise some of the parameters of the model so that the model may provide correct predictions.**

I. Introduction

The advent of the digital computer and the parallel development of software have dramatically changed the possibilities in design and development of systems since several decades, in particular in control applications. Indeed, simulations on the digital computer enable systems to be studied at relatively low cost and without the embarrassment associated with on the field experimentation. However, to be able to use a computer for simulation requires a model of the problem that can be implemented on the digital computer.

Models of actual systems can be analytical or empirical. Analytical or mathematical models are based on well-established physical and/or chemical laws, such as mass, momentum and energy conservation laws, equations of states for gases, etc. A mathematical model of a dynamic system is defined as a set of equations that represents the dynamics of the system accurately or, at least, fairly well [1]. However, a mathematical model is not unique to a given system. A system may be represented in many different ways and, therefore, may have many mathematical models, depending on one's perspective. Empirical models, on the other hand, are based on input and output data. The use of neural networks, for instance, to model processes fall into that category [2]. The empirical model is very often a black box model that tries to map the input data to the output ones. For these black box models to be valid, huge amount of information about all the inputs and outputs must be available. In addition, such models are obscured to a person and a model obtained and validated for a particular system cannot be applied, at least not easily, to another of the same family.

However, very often, complete input output data about a system are not available, or some of the data are not trustworthy but an analytical model that describes accurately enough the dynamics of the system is available. In such cases, physical parameters about the system must be known to be able to use the analytical model to predict the output or outputs given the inputs.

The performance of a mathematical model in regard to the prediction of the values of the output variables might not be satisfactory even if the values of the physical parameters of which the model is constituted were available. Indeed, in deriving an analytical mathematical model of a plant, a compromise is often made between the simplicity and the accuracy of the model. There are reasons for developing a simple model among which are limited amount of time and computing power. Nonetheless, the mathematical model, theoretically, might be representing the dynamics of the plant adequately enough. The discrepancy between available plant data and the predicted model data most probably is because of the assumptions made to simplify the model. Consequently, for the mathematical model to be useful, some of the physical parameters must be estimated.

This paper proposes a hybrid approach to the modelling of dynamic systems. The approach exploits the advantages of both the analytical mathematical modelling and the empirical modelling. The Genetic Algorithms (GA) is used to estimate and tune some physical parameters and variables of a mathematical model. The approach is applied to a multiple-effect evaporator (MEE) in the sugar industry. The MEE process is particularly suited to show the usefulness of this approach because of the difficulty of estimating the physical parameters due to the severe interactions of mass ad energy across the whole process.

This paper is organised as follows. Section II describes the MEE process on which the proposed approach is tested. Section III presents a mathematical model of the MEE. In section IV, the approach using GA to extract the plant parameters and to tune the model is presented. In section V, results are given with some discussion while section VI presents some conclusions.

II. Multiple-Effect Evaporation Process

A. *Principle of Multiple Effects*

When juice is heated by steam in an evaporator, a quantity of juice steam, approximately equal to the amount of steam condensed in the condensation chamber, is produced. This juice steam, which is at a lower temperature and pressure, can be utilised in turn as heating steam for a second evaporator. The juice steam from the latter evaporator can be used to heat a third evaporator and so on. This is the principle of multiple-effect. The number of effects is equal to the number of unit evaporators. To provide the necessary temperature difference for heat to flow from the first to the last effect, the last effect is connected to a vacuum pump. Thus, the pressure along the effects decreases monotonically from the first to the last.

B. Condenser

The juice steam from the last effect is usually sent to a direct contact condenser. This steam is not re-circulated in the factory and is therefore lost. The vacuum pump required to raise the necessary vacuum is connected to the condenser. The hot water exiting from the condenser is sent to a cooling pond where the temperature of the water is reduced before being recirculated in the condenser.

C. Vapour Bleeding

A sugar factory is a big consumer of low pressure heating steam; the latter is required by the juice heaters to heat the raw juice coming from the mills and the clarified juice, and in the vacuum pans. There is a gradual decrease in temperature and pressure along the MEE. The MEE thus offers a complete range of vapour temperatures, which can satisfy different heating purposes. Since many heating apparatus in the factory requires only low-pressure steam, it is more economical to bleed vapour from the intermediate effects in a MEE instead of using live steam. Thus, the heaters and the MEE are dependent.

D. Presentation of MEE Station

The MEE process considered in this paper is depicted in Fig. 1. It consists of five effects (Roberts) with vapour bleeding from the second, third and fourth effects only. The heating steam in the first effect is exhausted from the turbo-alternator in the factory. The juice steam from the last effect is sent to a direct-contact condenser. The major part of the vapour bleeding takes place in the second effect, which supply the vacuum pans with heating steam, in addition to a juice heater.

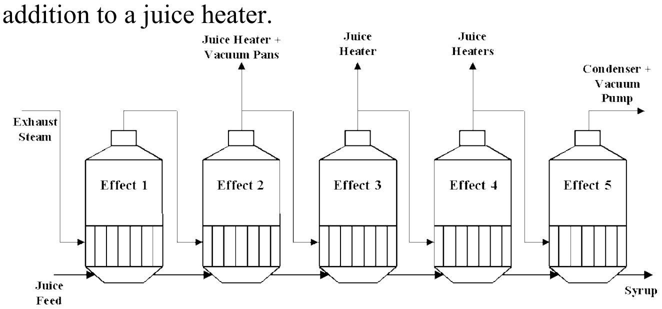

Fig. 1. Multiple-Effect Evaporator Station

III. MODEL PRESENTATION

A. Analytical Mathematical Model

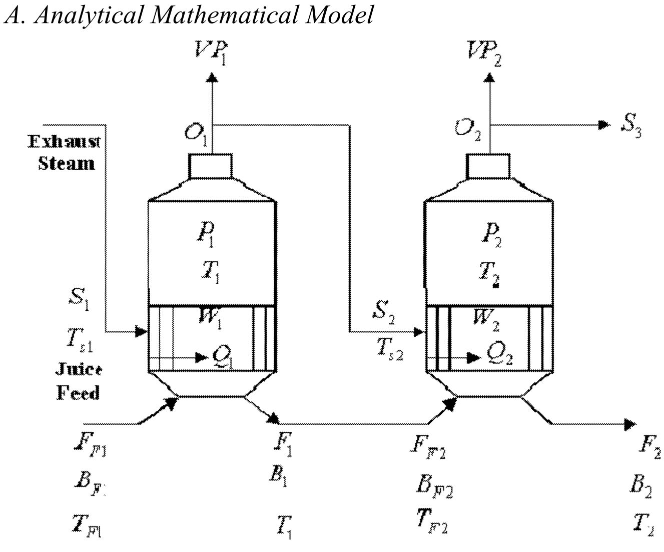

Fig. 2. First two Effects Illustrating Mathematical Modelling

The overall model of the MEE station is obtained by the concatenation of the models of each evaporator. The model of the evaporator is built from mass and energy balances. This approach provides a lot of flexibility of developing general unit models because the model of any MEE station can be built up. However, the order of the resulting models is generally high and some form of model order reduction becomes necessary [3].

One intuitive way to reduce the order of the model is to make reasonable assumptions. The following basic assumptions have been made:

1. The heat-of-solution effects of the juice/syrup in the effects are assumed negligible.
2. Zero boiling point rise in the solution due to hydrostatic pressure.
3. Saturated steam in all vapour space. This enables the use of steam tables directly.
4. Identical conditions throughout the steam chest and connected vapour space.
5. No subcooling of the steam condensate streams so that the heat transfer to the solution hold-up is only the latent heat of condensation and which is much easier to determine.
6. The heat losses to the environment are negligible.
7. Zero concentration of solute in the overhead vapour streams so that the vapour is pure and saturated.
8. Negligible heat capacity in the evaporator vessels and piping so that the dynamics of the tube bundle in each evaporator may be neglected.
9. The mass of juice/syrup in the concentration chamber of an effect is constant.
10. Phase equilibrium between vapour and juice/syrup exists at all time.

A mass balance around the liquid holdup in the tubes gives

$$F_{Fi} = F_i + O_i \qquad \textbf{(1)}$$

where

F_{Fi} = mass flow rate of juice feed into an effect (kg/s)

F_i = mass flow rate of juice/syrup out of effect (kg/s)

O_i = mass flow rate of overhead juice steam out of effect (kg/s)

A mass balance on the overhead vapour flow gives

$$O_i = VP_i + S_{i+1} \quad i = 1-4 \qquad \textbf{(2)}$$

where

VP_i = juice steam deduction (kg/s)

S_{i+1} = juice steam consumption by next effect (kg/s)

A solute balance around the liquid holdup in the concentration chamber gives

$$\frac{d}{dt}\left(W_i \cdot B_i\right) = F_{Fi} \cdot B_{Fi} - F_i \cdot B_i \qquad \textbf{(3)}$$

where

W_i = mass of liquid in concentration chamber (kg)

B_i = brix of juice/syrup leaving effect (mf)

B_{Fi} = brix of juice/syrup entering effect (mf)

from which the brix of the juice or syrup from each effect can be determined.

An energy balance around the liquid holdup in the evaporator gives

$$\frac{d}{dt}\left(W_i \cdot h_i\right) = F_{Fi} \cdot h_{Fi} - F_i \cdot h_i - O_i \cdot H_{vi} + Q_i \quad \textbf{(4)}$$

where

h_{Fi} = Enthalpy of juice/syrup entering effect (J/kg)

h_i = Enthalpy of juice/syrup leaving effect (J/kg)

H_{vi} = Enthalpy of juice steam leaving effect (J/kg)

Q_i = Heat flow from condensation to concentration chamber (J/s) or (W)

The heat flow from the condensation chamber to the concentration chamber is given by the transport equation

$$Q_i = U_i \cdot A_i \left(T_{si} - T_i\right) \quad \textbf{(5)}$$

where

U_i = overall heat transfer coefficient $\left(\mathrm{W/m^2K}\right)$

A_i = overall heat transfer area $\left(\mathrm{m}^2\right)$

T_{si} = temperature of heating steam $\left(°\mathrm{C}\right)$

T_i = temperature of liquid in concentration chamber $\left(°\mathrm{C}\right)$

The juice steam consumed by the next effect is given as

$$S_i = \frac{Q_i}{\lambda_{ci}},\ i = 2...5 \quad \textbf{(6)}$$

where

λ_{ci} = latent heat of condensation $\left(\mathrm{J/kg}\right)$

and is a function of the temperature assuming saturated conditions

$$\lambda_{ci} = f\left(T_{i-1}\right),\ i = 2...5 \quad \textbf{(7)}$$

The juice enthalpy for sugar cane juice is assumed to be of the simple form

$$h = c \cdot T$$

where c is the specific heat capacity. The enthalpy is given as [4]

$$h = 4186.8 \cdot T - 25.1208 \cdot B \cdot T + 0.07536 \cdot B \cdot T^2 - 0.03349\left(100-\alpha\right) \cdot B \cdot T \quad \textbf{(8)}$$

where it is seen that it is a function of the sugar concentration, B, and the temperature, T. α is the purity of the juice and is assumed constant at 90% in this paper. The following expressions can therefore be written [5]

$$\frac{dh}{dt} = \frac{\partial h}{\partial B} \cdot \frac{dB}{dT} + \frac{\partial h}{\partial T} \cdot \frac{dT}{dt} \quad \textbf{(9)}$$

$$\frac{\partial h}{\partial T} = 4186.8 - 25.1208 \cdot B + 0.15072 \cdot B \cdot T - 0.03349 \cdot \left(100 - P\right) \cdot B \quad \textbf{(10)}$$

$$\frac{\partial h}{\partial B} = -25.1208 \cdot T + 0.07536 \cdot T^2 - 0.03349 \cdot \left(100 - P\right) \cdot T \quad \textbf{(11)}$$

After substitution, the equations (3) and (4) can be expressed more appropriately as

$$\frac{dB_i}{dt} = \frac{F_{Fi} \cdot \left(B_{Fi} - B_i\right) + O_i \cdot B_i}{W_i} \quad \textbf{(12)}$$

$$\frac{dT_i}{dt} = \frac{F_{Fi} \cdot \left[\left(h_{Fi} - h_i\right) - \frac{\partial h_i}{\partial B_i} \cdot \left(B_{Fi} - B_i\right)\right] - O_i \cdot \left[H_{vi} - h_i + \frac{\partial h_i}{\partial B_i} \cdot B_i\right] + Q_i}{W_i \cdot \frac{\partial h_i}{\partial T_i}} \quad \textbf{(13)}$$

Since phase equilibrium has been assumed, the pressure is always equal to the vapour pressure of the liquid in the concentration chamber. Since sugar cane juice/syrup is a multi component liquor, the vapour pressure depends on both temperature and concentration and is given as

$$P_i = f\left(T_i, B_i\right) \quad \textbf{(14)}$$

where

P_i = vapour pressure in effect $\left(\mathrm{Pa}\right)$

B. Multieffect Model Building

To construct a complete process model of a MEE, algebraic configuration relationship must be written for each process stream connecting the units [3]. Thus, we have

$$F_{Fi+1} = F_i \ \ i = 1-4 \quad \textbf{(15)}$$

$$B_{Fi+1} = B_i \ \ i = 1-4 \quad \textbf{(16)}$$

$$T_{Fi+1} = T_i \ \ i = 1-4 \quad \textbf{(17)}$$

$$T_{si+1} = T_i \ \ i = 1-4 \quad \textbf{(18)}$$

It can thus be seen that the brix and the temperature are state variables of the model. The presented model, which is a non-linear one, is implemented directly into Simulink using available blocks. Relations (7) and (14) are implemented using look-up tables developed from data obtained from a saturated steam table and [6] respectively. These equations are solved at each integration step.

From the above mathematical model, it can be seen that the performance of the model in predicting the outputs depend on many effects because of the clear interactions that exists among the effects.

IV. SIMULATION OF MATHEMATICAL MODEL WITH PLANT DATA

The values of variables and constants obtained from an actual MEE in industry are shown in Table I and II, respectively. The heat transfer coefficients (HTCs), which in reality depend on several process factors, such as juice and steam flow rates, have been considered, for simplicity, as constant in this paper.

TABLE I
VARIABLES CONSIDERED IN MULTIPLE-EFFECT EVAPORATION PROCESS

Effect i	S_i (kg/s)	O_i (kg/s)	VP_i (kg/s)	P_i (kPa)	T_i (°C)	B_i (%)
1	10.0278	10.2222	0	141	110	18.05
2	10.2222	10.2222	5.7222	107	102	27.90
3	4.5	4.5	1.0833	53	83	37.55
4	3.4167	3.4167	0.9722	36	73	50.00
5	2.444	2.6389	0	16	55	66.20

The mathematical model of the MEE presented in the earlier section has been simulated with the data summarised in Table I and II above. The quality of the model as a tool for predicting the performance of the MEE and its use for the design of control systems shall be assessed based on the accuracy of the prediction of the values of the output variables compared with the corresponding plant data. In particular, the model must predict accurately enough the output variables, especially the state variables temperature T_i and the brix B_i, given the inputs in Table I.

TABLE II
CONSTANTS CONSIDERED IN MULTIPLE-EFFECT EVAPORATION PROCESS

Name	Value	Name	Value(m^2)	Name	Value(W/m^2K)
T_{s1}	117 (°C)	A_1	1200	U_1	2410
T_{F1}	114 (°C)	A_2	1400	U_2	2160
B_{F1}	13.44 (%)	A_3	750	U_3	750
		A_4	750	U_4	1210
		A_5	750	U_5	490

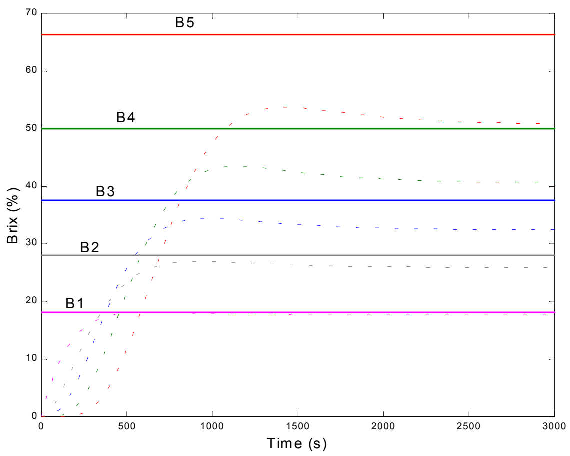

Fig. 3. Comparison of actual brix measured at factory with brix predicted by model with plant data. Solid lines represent actual brix measured at factory. Dotted lines are the brix predicted by the model before GA tuning.

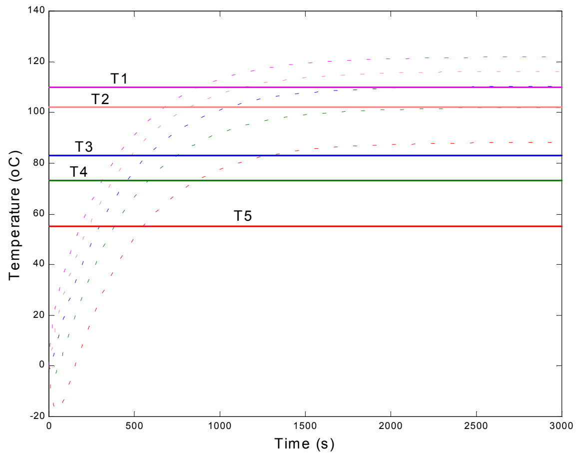

Fig. 4. Comparison between actual temperatures measured at factory with temperature predicted by model with plant data. Straight lines represent actual temperature. Dotted lines are the temperature predicted by the model before GA Tuning.

Figs. 3 and 4 shows the results for brix and temperature, respectively. It can clearly be seen that the model with the raw parameters obtained from factory cannot predict the values of the output variables accurately. It can be observed that all the predicted temperatures are above the actual values at steady state. However, there is only a small discrepancy between the predicted brix of the first effect and the actual measured brix but a big one for the fifth effect. It can thus be concluded that small deviations of the brix from the desired value are amplified along the MEE. This is where the adjustment of the physical parameters of the MEE becomes complicated because of the severe interactions among the units.

One of the critical physical parameter that needs to be adjusted is the HTC of the effects. Unfortunately, because of the interactions among the variables, tuning the HTCs alone would not guarantee the accuracy of the model. Therefore, it was decided to trust only some of the plant data while assuming others inaccurate. Since temperatures, pressures and brix of each effect are easily measured at the factory, it was assumed that these data are trustworthy and are taken as reference. On the other hand, the steam flow into the first effect, the juice steam flow from the fifth effect and the juice steam bled off from the second, third and fourth effects are considered inaccurate. All other variables and constants were left unchanged.

V. GA PLANT PARAMETER EXTRACTION AND MODEL OPTIMISATION

A. *Using Genetic Algorithms to Estimate Plant Parameters and Variables*

The model parameter selection boils down to an optimisation problem where the temperatures, pressures and brixes of each effect are optimised by finding the optimum values of HTCs and vapour flow rates. To be able to use a GA to tune the model, it is necessary to define a codification for the model parameters and a fitness function.

1) *Codification of Problem for Optimisation by GA*: There are nine parameters (4 HTCs and 5 steam flows) to optimise. These nine parameters are concatenated to form a chromosome. Real numbers are used to code the

chromosome [7], [8]. Table III shows the order of the parameters in the chromosome together with the lower and upper limit between which the GA is allowed to evolve the parameters. The GA parameters are: Maximum number of generation = 50, Population size = 40, Generation Gap = 0.9, Crossover Rate = 0.7 and Mutation Rate = 0.1.

TABLE III

CODIFICATION OF CHROMOSOME FOR GA

3000	2000	2000	1000	20	10	5	5	5
U_2	U_3	U_4	U_5	S_1	VP_2	VP_3	VP_4	O_5
500	500	500	300	5	4.1667	0.5	0.5	1

2) *Fitness Function*: To evaluate the effectiveness of each set of parameters, the process simulation has been used. The simulation was run for 3000 seconds, just sufficient to allow the transients to die out and the variables to reach steady state. To find the optimum values of the parameters, the steady state values of brix, temperature and pressure from the plant data must be reached. Then the GA must minimise the error between the actual plant data and the predicted model data. The smaller the error, the better would be the parameters the GA has evolved. This is a multiobjective optimisation problem. In order to solve this problem using a simple GA, the reference objectives were reformulated as a single minimax function [9].

B. *Parameters and Variables of Tuned Model*

Table IV gives the HTCs and the steam flow rates identified by the GA. Table V gives the values of brix, temperature and pressure predicted by the model before and after tuning. In addition the reduction in the error with respect to the reference values are given.

TABLE IV

COMPARISON OF HTCS AND STEAM FLOW RATES OBTAINED FROM FACTORY AND IDENTIFIED BY GA

	HTC (W/m^2K)				Steam Flows (kg/s)				
	U_2	U_3	U_4	U_5	S_1	O_5	VP_2	VP_3	VP_4
Factory	2160	750	1210	490	10.0278	2.6389	5.7222	1.0833	0.9722
GA	1732.1336	785.04184	1123.2762	513.27317	9.2609	2.9346	4.8662	1.5576	1.4249

What is striking in these results is that although the values estimated by the GA are not exactly equal, as expected, to the values obtained from the factory, the order of the magnitude of both the HTCs (U) and the steam flow rates (VP) relative to each other is maintained. As for the results of the tuned model, they are much better as evidenced by the drastic decrease in error (Table V).

TABLE V

REDUCTION IN ERROR BETWEEN PREDICTED AND REFERENCE VARIABLES AFTER TUNING MODEL BY GA OVER 50 GENERATIONS

		Effect No.				
		1	*2*	*3*	*4*	*5*
Brix (%)	Ref. Value	18.05	27.90	37.55	50.00	66.20
	Before Tuning	17.38	24.93	30.87	38.04	46.79
	After Tuning	17.49	25.49	34.22	46.21	61.86
	Improvement (%)	***-16.42***	***-18.86***	***-50.15***	***-68.31***	***-77.64***
Temperature (oC)	Ref. Value	110.0	102.0	83.00	73.00	55.00
	Before Tuning	128.1	121.5	107.30	99.75	85.55
	After Tuning	113.4	104.9	86.68	76.28	60.32
	Improvement (%)	***-81.22***	***-85.13***	***-84.86***	***-87.74***	***-82.59***
Pressure (kPa)	Ref. Value	141	107	53	36	16
	Before Tuning	176.5	156.7	116	94.12	55.91
	After Tuning	134.9	109.9	59.61	38.61	18.04
	Improvement (%)	***-117.18***	***-94.16***	***-89.51***	***-95.51***	***-94.89***

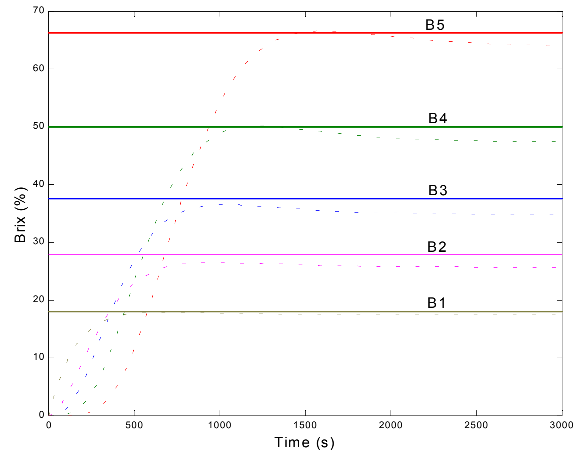

Fig. 5. Output of GA tuned model for brix.

Fig. 5 and fig. 6 shows the predictions of the tuned analytical model of the MEE and the actual measured outputs. Now it can be observed that the GA tuned model approximates better the actual plant. The curves for both temperature and brix get closer to the actual plant data. This clearly shows that the new values of HTCs and the vapour flow rates into and out of the effects are better suited to the present mathematical model than those obtained from the factory.

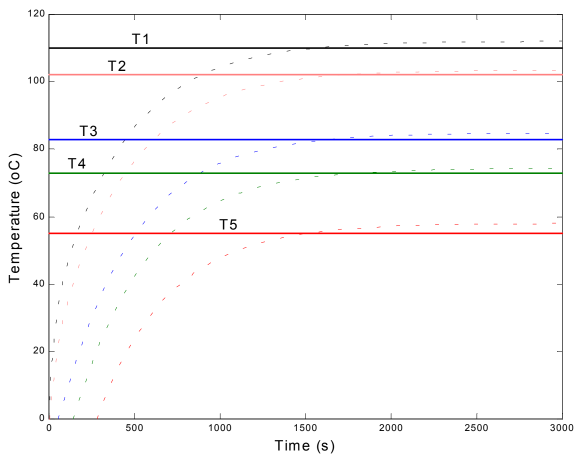

Fig. 6. Model: GA Tuned. Output: Temperature. Solid lines: Actual Plant Data. Dotted lines: Predicted Model Data

C. *Shifting Model of MEE to new Operating Point*

With high performance control systems, the control variables of the MEE can be maintained tightly at optimum setpoints. The main controlled variable in the MEE of a sugar factory is the brix of the syrup at the exit of the last effect. For economic reasons, the brix should be as high as permissible thus giving maximum possible evaporation. This renders the vacuum pans more efficient because less water then needs to be evaporated in them [10]. However, the brix should not be too high because then sugar will start crystallising inside the tubes. It is recommended that the final brix should be 72% for economic reasons as mentioned above but also because of other reasons [4]. In addition, since a MEE in the sugar industry works under vacuum, the temperature in the last effect is usually around 55 ^{0}C.

Having obtained the HTCs and the vapour bled off from each effect, they are now assumed to remain constant as long as the juice feed at the first effect does not change significantly. To raise the brix B5 to 72% while maintaining the temperature T_5 at 55 ^{0}C, the GA is again used to find the new corresponding optimum values of S_1 and O_5. The objective function is to minimise the error between the required B5 and T_5 and the actual values predicted by the model. Since there are two objective functions, the minimax strategy is again applied. However, this time the chromosome of the GA is made up of a concatenated string of S_1 and O_5 only. The limits of the two parameters and the GA parameters are as before. After 50 generations of evolution, the GA came up with S_1 = 9.3818 $\mathrm{kg/s}$ and O_5 = 3.1755 $\mathrm{kg/s}$. Obviously S_1 and O_5 are higher because the setpoint of the brix5 is set higher so that more water needs to be evaporated. To evaporate the additional water to achieve the higher brix more exhaust steam may be admitted into the first effect, the vacuum at the fifth effect may be increased or both operations may be done simultaneously but to different degrees. From the results, it can be seen that the GA has come up with the last solution by increasing both the steam S_1 and the overhead vapour flow rate O_5, which makes sense.

Table VI summarises the values of some of the variables in the MEE at the new operating point.

TABLE VI

NEW STEADY STATE VALUES FOR MULTIPLE-EFFECT EVAPORATOR

Effect, i	**Temperature, T_i (°C)**	**Brix, B_i (%)**	**Pressure, P_i (kPa)**	**Juice Flow, F_i (kg/s)**	**Steam Flow, S_i (kg/s)**
1	**111.6**	**17.62**	**129.8**	**30.51**	**9.3818**
2	**102.9**	**26.07**	**104.2**	**20.62**	**9.494**
3	**83.69**	**35.87**	**53.11**	**14.99**	**5.021**
4	**72.57**	**50.41**	**32.55**	**10.67**	**4.073**
5	**55.05**	**71.78**	**13.96**	**7.490**	**2.899**

V. CONCLUSIONS

This paper has presented a hybrid approach towards the derivation of the modelling of processes. Most mathematical models are based on certain assumptions, which render them inaccurate to some extent. To be able to use these models in simulation, physical parameters about the model must be known. However, although the model might be capturing the major dynamics of a plant fairly well, the outputs for given inputs might be very deceiving because the available physical parameters might not be appropriate for the chosen level of abstraction of the mathematical model. This is where the hybrid approach using GA is relevant.

Unlike the derivation of black-box models which require large quantities of input-output data, the proposed approach require only some data, which can be considered to be accurate enough, to estimate and tune some parameters of a mathematical model that is guaranteed to represent sufficiently the essence of the plant. In this paper the proposed approach has been verified on a MEE station which has a lot of interactions and several parameters and variables. The results showed that the approach could indeed be very useful. In addition, the technique could be used to find the values of variables at other operating points.

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