International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 3 Issue 8, August - 2014

Artificial Neural Network Based Modeling and Control of Bioreactor

Ballekallu Chinna Eeranna* Subba Rao**,G. Prabhaker Reddy**
*Dept.of petroleum Engineering, Lords institute of engineering and Technology
**Dept. of Chemical Engineering, University College of Technology,
Osmania University, Hyderabad,

Abstract: In this paper presents about control of Bioreactor useing Artificial Neural Network. bioreactor has become an active area of research in recent years. This is partially attributable to the fact that bioreactors can be extremely difficult to control. Their dynamic behavior is invariably non-linear and model parameters vary in an unpredictable manner. Accurate process models are rarely available due to complexity of the underlying biochemical processes. A feedback controller is needed to account for disturbances and time-varying behavior. Neural network based model predictive controller designed for the control of bioreactor. In the first step the neural network model of bioreactor is obtained by levenburg- marquard training the data for the training the network generated using mathematical model of bioreactor.

Keywords: Neural network model predictive control, bioreactor,productivity.

INTRODUCTION

A control system is defined as a system in which deliberate guidance or manipulation is used to achieve a prescribed value of a variable. In the last two decades, a new direction to control has gained considerable attention. This new approach to control is called 'Intelligent control'. The term 'conventional control' refers to theories and methods that are employed to control dynamic systems whose behavior is primarily described by differential and difference equations. The term 'intelligent control' addresses to more general control problems. It may refer to systems, which cannot be adequately described by a differential equations framework. There are three basic approaches to intelligent control knowledge-based experts systems, fuzzy logic and neural networks.

2.FERMENTATION:

Most of the processes in the biotechnology industry have time-varying parameters and are inherently non-linear. Because of that, the implementation of the classical modeling and control techniques is very difficult. Moreover, it has been recognized for some time, that the observed cell population at a certain time-instant is the combined effect if various biological processes that had been initiated at different moments in the past. The processes are affected by the instantaneous environmental conditions prevailing at each particular past time. Hence the kinetics of fermentation process should be considered as depending not only on the current Process State, but also on the weighted average of the states at the past moments, i.e., of the culture memory.

The main factors contributing the difficulty in modeling and control of bioreactors are:

1) Their dynamic behavior is inherently non-linear.
2) Accurate process models are not available due to the complexity of the underlying biochemical process.
3) Model Parameters vary with in an unpredictable manner.
4) Reliable biosensors to measure intercellular activities are rarely available, making the Process State very difficult to characterize.

3. CONTINUOUS BIOREACTORS:

In most of the continuous fermentation processes, one of the output variables is chosen as the controlled variable (biomass concentration or product concentration) and its estimated optimal open loop profile of a constant set point is tracked. A continuous stirred tank fermenter (CSTF) is an ideal reactor, which is based on the assumption that the reactor contents are well mixed

4. PROBLEMS WITH THE CONVENTIONAL CONTROLLER:

The control of non-linear process like fermentation by conventional controller does not give satisfactory results. This is due to the change in process gain and time constant with operating conditions. In certain processes, more than one value of a manipulated variable (u) produces the same value of an output variable. Such situation is called as input multiplicities. The value of the steady-state gain of the process changes as the manipulated variable changes and after certain value of u the sign of the gain value also changes . The controller tuned at one operating condition may even destabilize the system at another operating point. Di Biasio et al., (1994) have reported that the global stability of the reactor depends on the existence and stability of the other steady conditions. The performance on the closed system is compared with that of a linear P1 proposed by Henson and Seborg any constraint on the manipulated variable (which is often unavoidable in practice) can result in a total of 5 steady states (three stable

and two saddle points) even though a sufficient control action is present.

5. CONTROL OF BIOREACTORS USING NEURAL NETWORK:

The inherent non-linearity of the fermentation process often renders control difficult. Neural network has become popular tool for modeling and control of dynamic process, demonstrating the ability of handling non-linearity. Many neural network controllers are of the rule-based type where the controller's output response is described by a series of control rules.

The unique features of this neural network control technique include:

- A wide operation range for handling a non-linear process.
- Robustness for dealing with random disturbance and possible system parameter Drafting.
- Relatively simple implementation.

In the present work, neural network control is designed and evaluated for the continuous bioreactor with one input and one output to overcome the control problems associated with linear P1 controller due to the input multiplicity.

6. MATHEMATICAL MODELLING OF A CONTINUOUS BIOREACTOR

A schematic of a continuous bioreactor is shown in figure 3.1-We assume that the bioreactor has constant volume, its contents are well mixed, and the feed is sterile. The dilution rate D and the feed substrate concentration Sf are available as manipulated inputs. The effluent cell-mass or biomass concentration X, substrate concentration S and product concentration P are the process state variables. In ethanol production, for example, X, Y, and P represent yeast, glucose, and ethanol concentrations, respectively.

Many models have been proposed for fermentation processes. Structured models attempt to describe the individual organisms in detail but are usually mathematically too complex to be useful for controller design. Significantly simpler unstructured models can be obtained by assuming that the bioreactor culture consists of a single, homogeneously growing organism. These models usually consist of a few nonlinear ordinary differential equations and are particularly well suited to the nonlinear control strategies.

6.1 MODEL DERIVATION:

The dynamic model is developed by writing material balances on the biomass (cells), the substrate (feed source for cells) and the product. Biomass grows by feeding on the substrate results in generation of product.

Biomass Material Balance

We write biomass material balance as:

Rate of accumulation = i/p – o/p + generation

$d(VX)/dt = FXf - FX + Vr1$ (1)

Substrate Material Balance:

The substrate material balance is written as:

$d(VS)/dt = F\,Sf - FS - Vr2$ (2)

Product Material Balance:

Finally, the product material balance is written as:

$D(VP)/dt = 0 - F\,P + Vr3$ ¬ (3)

The reaction rate (mass of the cells generation/Volume/time) is normally written in the following form: $r1 = \mu X$ (4)

As yield $Y = r1/r2$, $r2 = r1/Y$

And hence $r2 = \mu X/Y$ (5)

Similarly $r3 = (\alpha\mu+\beta) X$ (6)

Defining F/V as D, the dilution rate, and assuming biomass feed concentration as Zero,Finally, the model equations can be written as;

$X = -DX + \mu X$ (7)

$S = D(Sf - S) - \mu X/Y$ (8)

$P = -DP + (\alpha\mu + \beta) X$ (9)

This unstructured model can describe a variety of fermentations. Because Y, and P are assumed to be independent of the operating conditions, above model is called a constant yield model. The specific growth rate model is allowed to exhibit both substrate and product inhibition:

$$\mu = \frac{\mu_m (1 - P/P_m) S}{K_m + S + S_2/K_1} \quad (10)$$

This model contains four model parameters: the maximum specific growth rate m, the product saturation constant Pm, the substrate saturation constant Km, and the substrate inhibition constant K1.

Model equation of the system on which the study is based:

$$X = -DX + \mu X$$

$$S = D(S_f - S) - \mu X/Y$$

$$P = -DP + (\alpha\mu + \beta) X$$

$$\mu = \frac{\mu_m (1 - P/P_m) S}{K_m + S + S_2/K_1}$$

In practice, the model parameters in equations (7)-(10) are chosen to fit experimental data (Munack and Thoma, 1986; Enfors et a!., 1990). If the bioreactor deviates significantly from the operating conditions where the data was collected, the model parameters previously determined may no longer be valid. The cell-mass yield Y and the maximum specific growth rate tm tend to be especially sensitive to changes in the operating conditions. From a process control

perspective, these two model parameters can be viewed as unmeasured disturbances because they may exhibit significant time-varying behavior. Many types of fermentations can be modeled by choosing the model parameters appropriately . For instance, the product is totally growth-associated if a $\alpha \neq 0$, $\beta = 0$, totally non growth-associated if a = 0, $\beta \neq 0$, and a combination of the two if $\alpha \neq 0$, $\beta \neq 0$. Simple Monod kinetics (Johnson, 1987) can be obtained by setting Pm = K1 =α 'c. In many fermentations such as penicillin production, cell growth is inhibited by high substrate concentrations so that 0 < K1 < cc. If the growth rate approaches zero at high product concentrations then 0 <Pm < α.

Nominal model parameters and operating conditions used throughout the study are listed below:

Variable	Nominal value
Y	0.4 g/g
A	2.2 g/g
B	0.2 h^{-1}
μ_m	0.48 h^{-1}
P_m	50 g/1
K_m	1.2 g/1
K_1	22 g/1
S_f	20 g/1

If the biomass and substrate are of negligible value when compared to that of the product, the productivity Q can be defined as the amount of product cells produced per unit time:

$$Q = DP \quad (11)$$

7. DESIGN OF NEURAL NETWORK MODEL PREDICTIVE CONTROLLER OF BIOREACTOR

The neural network predictive controller that is implemented in the neural network toolbox software uses a neural network model of a nonlinear plant to predict future plant performance. The controller then calculates the control input that will optimize plant performance over a specified future time horizon.

Predictive control

The model predictive control method is based on the receding horizon technique. The neural network model predicts the plant response over a specified time horizon. The predictions are used by a numerical optimization program to determine the control signal that minimizes the following performance criterion over the specified horizon.

$$J = \sum_{j=N_1}^{N_2} (y_r(t+j) - y_m(t+j))^2 + \rho \sum_{j=1}^{N_u} (u'(t+j-1) - u'(t+j-2))^2 \quad (11)$$

Where N1, N2, and Nu and define the horizons over which the tracking error and the control increments are evaluated. The u' variable is the tentative control signal, yr is the desired response, and ym is the network model response. The p value determines the contribution that the sum of the squares of the control increments has on the performance index.

The following diagrams illustrates the model predictive control process. The controller consists of the neural network plant model and the optimization block. The optimization block determines the values of u' that minimize J, and then the optimal u is input to the plant. The controller block is implemented in Simulink, as described in the following section.

8. SIMULATION RESULTS & DISCUSSIONS

The performance of proposed neural network controller and conventional PI controller to the continuous bioreactor with input multiplicities in dilution rate is evaluated using the closed loop block diagram as shown fig. this block diagram essentially is prepared in the simulation MATLAB, its associated tool simulink and the NEURAL NETWORK toolbox have been used.

The simulation studies for regulatory and servo problem have been presented below.

8.1 LOWER DILUTION RATE (D =0.09368HR-1)

8.1.1 Servo problem:

The servo response has been studied by giving a step change in set point of productivity with direct inverse neural network and PI controller.

At lower dilution rate the servo problem has been analyzed by giving step change in set point of productivity from 3.0 to 3.1 and the corresponding responses are shown fig.6.Model predictive e control shows stable response at about 10hrs. Whereas PI reaches after 100 hrs .Its corresponding control action in terms of dilution rate is shown in fig. 7.

Fig 8 shows the step change in the set point of productivity from 3.0 to 2.9.In this response the NNMPC reaches the set point at around 20 hrs without any offset whereas PI is reaching the set point at 300 hrs.The corresponding manipulated variable in terms of dilution rate versus time behavior is shown fig 9

8.1.2 Regulatory problem:

The regulatory response in productivity of model predictive neural network controller and PI controller for dilution rate input of disturbance in feed substrate concentration have been studied and they are stated below:

The regulatory response in productivity of model predictive neural network and conventional PI is shown in fig 10 for a step change in feed substrate concentration from 20 to 24(+20%).This fig shows that the response of the model

predictive neural network controller is faster than that of the linear PI. Proposed neural network control has less deviation of 3% whereas conventional PI controller has a larger deviation of about 8%. model predictive neural network controller has low settling time than the PI controller. The corresponding control actions for manipulated variable in terms of dilution rate versus time behavior are shown in fig 11.

The regulatory response in productivity of model predictive neural network and conventional PI is shown in fig 12 for a step change in feed substrate concentration from 20 to 18(-10%).This fig shows that the response of the model predictive neural network controller is faster than that of the linear PI. Proposed neural network control has less deviation of 2% whereas conventional PI controller has a larger deviation of about 6%. model predictive neural network controller has low settling time than the PI controller. The corresponding control actions for manipulated variable in terms of dilution rate versus time behavior are shown in fig 13.

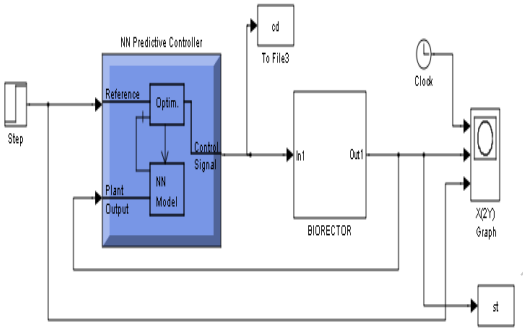


Fig.1. Block diagram of neural network model predictive controller

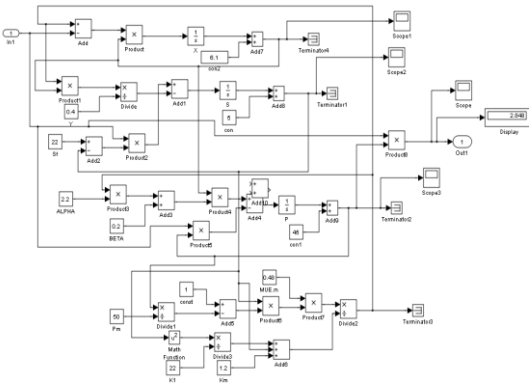


Fig 2.Block diagram of the subsystem of Bioreactor

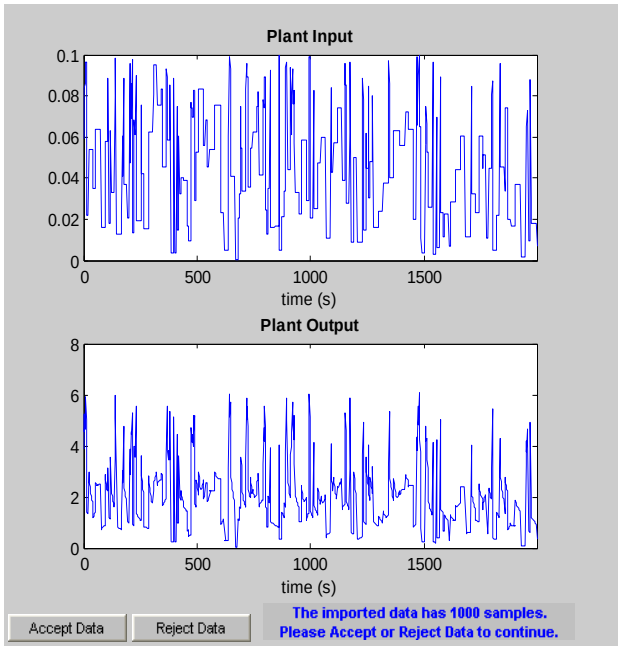


Fig. 3. Data generation of the neural network Model Predictive Controller

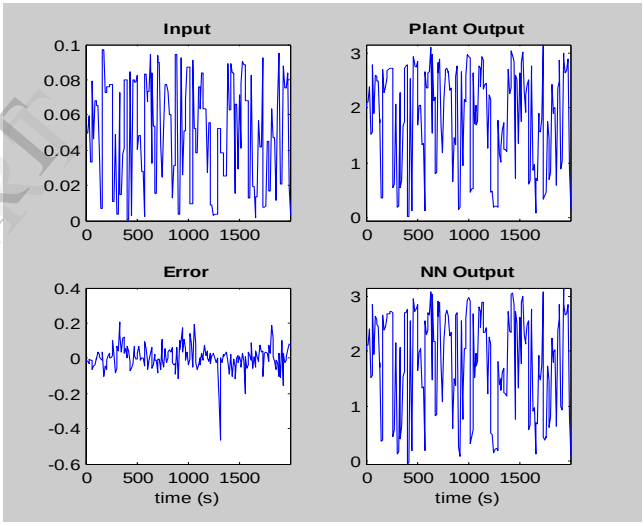
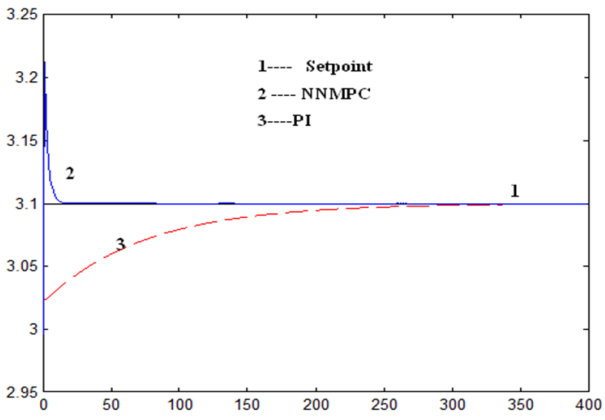
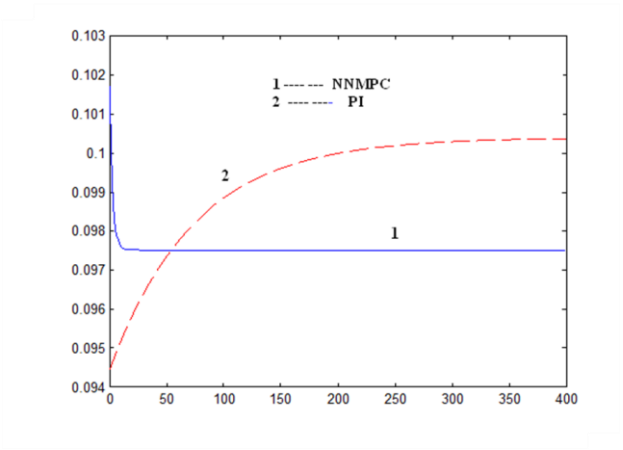


Fig .4. Trainig data for neural network predictive controller

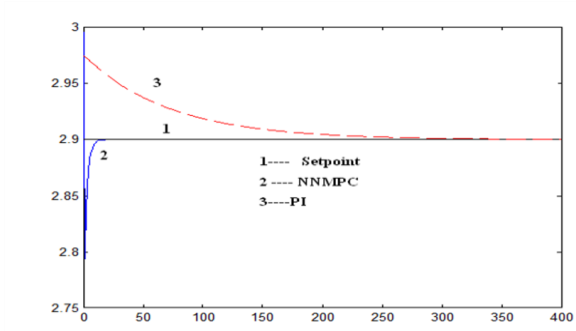


Time, hr

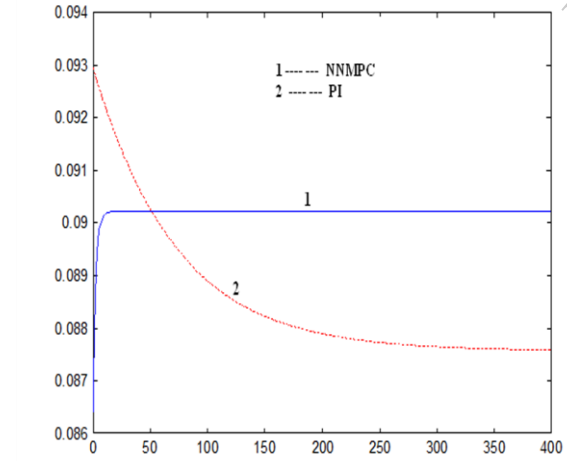
Fig 5. Closed loop response of productivity for step change in set point from 3.0 to 3.1 (+10%) at lower input



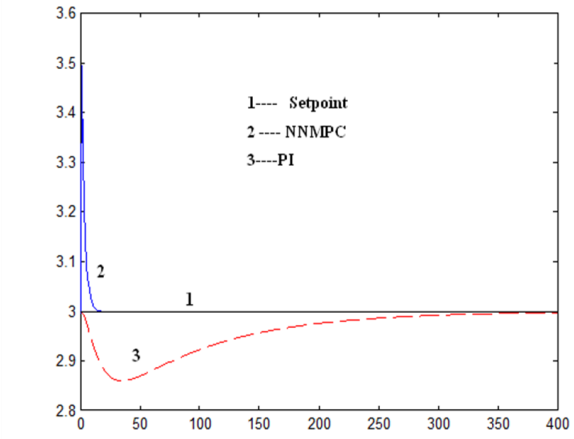
Time, hr
Fig 6 Control action in Dilution rate
Vs time as shown in fig 5



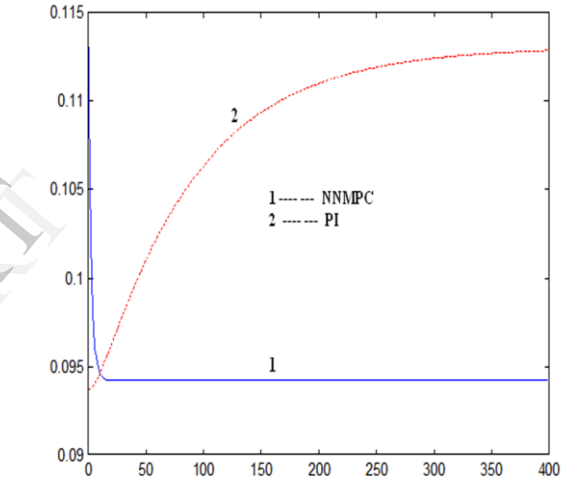
Time, hr
Fig 7. Closed loop response of productivity for step change in set point from 3.0 to 2.9 (-10%) at lower input



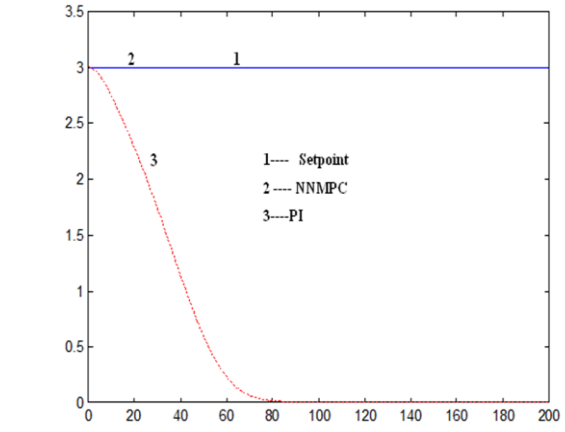
Time, hr
Fig 8 Control action in Dilution rate
Vs time as shown in fig 7



Time, hr
Fig 9 Productivity Versus time for change in Sf from 20 to 18 g/l at lower input



Time, hr
Fig 10 Control action in Dilution rate
Vs time as shown in fig 9



Time, hr
Fig 11 Productivity Versus time for change in Sf from 20 to 24 g/l at lower input

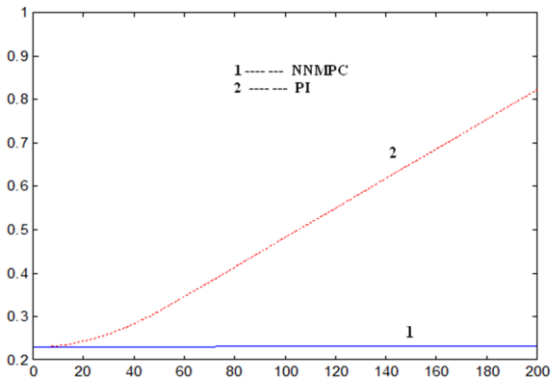


Fig 12 Control action in Dilution rate
Vs time as shown in fig 11

CONCLUSIONS

In the present work, the performance of conventional PI controller and Neural Network based controller is studied for the set point changes at lower input dilution rates. Based on the above studies the following conclusions are made.

At lower input dilution rate, response of PI controller for set point change from 3 to 3.1 g/l/h is stable with offset and for another set point change of 3 to 2.9 g/l/h is stable with offset response due to input multiplicities. Whereas proposed neural network based model predictive controller is giving stable

REFERENCES

[1]. Chidambaram,M and Reddy, G.P. (1995) Nonlinear control of systems with input multiplicities , Computers and Chemical Engineering, 19 pp249-252.

[2]. Abonyi, J ,.Babuska, R. and Ayala Botto, M and Szeifert, F L. Nagy and Nagy (2002) Identification and control of nonlinear systems using fuzzy hammerstein models, Industrial & Engineering chemistry Research.39 pp4302-4314 .

[3]. Dash, S.K. and Koppel, L.B.(1989) Sudden destabilization of controlled chemical Processes Chemical Engineering Communications, 84 , pp 129-157.

[4.] Koppel,L.B. (1982) Input multiplicities in nonlinear multivariable control systems AIChE Journal.28 pp935 -945.

[5.] Koppel, L.B.(1983) Input multiplicities in process control, Chemical Engineering Education, pp58-63, & 89-92.

[6]. D.B.Anuradha, G.Prabhaker Reddy and , J.S.N.Murthy, "Direct Inverse Neural Network Control of A Continuous Stirred Tank Reactor", Proc. IMECS, .2, Hong Kong,236-241,2009.

[7] M. A. Henson &.D.E. Seborg , "Nonlinear control strategies for continuous fermenter", Chemical engineering Science, 47,821-835, 1982.