

System Parameter Estimation using PSO Algorithm

Arun M K^[1], Biju U^[2], Neeraj Nair Rajagopal^[3], Prof. Bagyaveereswaran.V^[4],
SELECT,VIT UNIVERSITY, Vellore

Abstract—The paper proposes a new method of identifying a system by sample data. The identification technique involves the process of parameter estimation and application of PSO algorithm. Particle swarm optimization (PSO) aims to realize both structure and parameter identification of system in real time. The paper explains how the PSO is a better option for system identification process than other conventional algorithms.

Index Terms—PSO, combinatorial optimization, System Identification.

I. INTRODUCTION

System identification^[1] is a challenging task which determines a model from a set of several models based on the input and output data. It is an advanced process which defines a system mathematically through its physical working. Sample data based system identification is the most used method in these processes. System Identification can be done through analytical approach or through experimental approach. New identification methods have also been developed using genetic algorithm^[2], neural network, fuzzy logic, wavelet transform, et al. These methods have limitations that they fail when the structure and parameters of the systems are completely unknown. Optimization algorithms have helped in solving many problems like estimation bias, controller design, et al. Hence, we consider Particle Swarm Optimization (PSO) algorithm for identification problem.

Particle Swarm Optimization algorithm^[3] is an evolutionary technique used for optimization put forwarded by Kennedy and Eberhart in 1995. The algorithm is based on the predation of birds and swarm intelligence. The main attraction of this algorithm includes simple principle, fast convergence and easy implementation. The rapid convergence property and simple computation makes it applicable to various fields of studies. PSO is useful for parameter estimation which is a key step towards identification of systems^[7].

A system model is comprised of several mathematical models through inter combination. A fitness function is defined for each sub-model which is evaluated in the main program to find a local optimum and consequently a global optimum for the parameters of the system. Thus by using PSO algorithm, the structure and parameters of the model are identified. The effectiveness of

the method is verified by using simulation experiment of the model.

II. PARTICLE SWARM OPTIMISATION

This comes under the category of global random optimization^[4]. Here every solution is considered as a particle or bird in a search space or region. With an optimized function we determine fitness function of all particles given. The fastness of determining distance and the direction differs for every particle. For every iteration, iteration of particle depends on two extrema i.e. local extremum and global extremum. If both extrema are known, particle updates its velocities and position according to the formula,

$$v_{ij}(t+1) = w * v_{ij}(t) + C_1 r_1 (p_g - r_{ij}(t)) + C_2 r_2 (g_j - x_{ij}(t)) \quad (1)$$

$$x_{ij}(t+1) = v_{ij}(t+1) + x_{ij}(t) \quad (2)$$

Where,

w – inertial weight

$v_{ij}(t)$ – component of dimension no. ' j ' of velocity vector of particle ' i ' at time t ,

$x_{ij}(t)$ - component of dimension no. ' j ' of the position vector of particle ' i ' at time t ,

p_g - component of dimension no. ' j ' of the historically optimal position vector of particle ' i ' at time t ,

g_j - component of dimension no. ' j ' of the historically optimal position vector of particle swarm at time t ,

r_1, r_2 - two random numbers between 0 and 1

C_1, C_2 - group cognitive functions (correction factors).

III. DESIGN OF FITNESS FUNCTION

The aim of the system identification process is to fit a sample model with the original system in an optimal way. It means that the calculated system output y_{mk} should match the actual system output y_k as much as possible. So a criterion function should be taken for the validation of each output with the actual one^[5]. The cost function used here is,

$$y = \sqrt{\sum_{k=1}^n (y_k - y_{mk})^2} \quad (3)$$

Where

y_{mk} - the model output result of the sample data of i^{th} set of input-output

y_k - the actual output of known model for i^{th} set of input-output.

IV. PROCEDURE FOR SYSTEM IDENTIFICATION

System identification using PSO requires a lot of pre-processing stages before the actual identification^[7]. Below given are the main steps undertaken to achieve the same:

Step 1: This step consists of initialization of PSO parameters like number of 'birds', maximum number of 'bird steps', dimension of the problem (no. of parameters), correction factors and inertia.

Step 2: Initialising random variables $r1$ and $r2$ and the current fitness function.

Step 3: Initialize the swarm velocities and its positions. Current position is defined and the local best position is calculated. Velocity of the particle is also initialised.

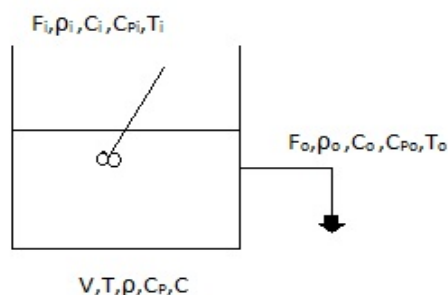
Step 4: Evaluate the initial population using the initialized parameters and the current position and proceed to next step.

Step 5: Now we evaluate for a new swarm where a current fitness function is defined through the initialized parameters and input-output data set. Assign it as the local best fitness and compare with the global best. If the new one is a global best then proceed to Step 6 or go back to Step 2.

Step 6: Velocity update- Velocity of each particle is updated using the equation (1) when the global best is found.

Step 7: Swarm update- current position is updated using the velocity obtained from the previous step. The whole procedure is repeated for 'n' iterations and an optimized function is obtained.

V. PROBLEM DESCRIPTION AND ANALYSIS



Figure(1). Experimental setup of CSTR

For experimental proof, we consider a first order continuous stirred tank reactor (CSTR) which is isothermal and has a constant volume as shown in figure(1). Here

F_i, F_o - Inlet, outlet flow

ρ_i, ρ_o - Densities of the inlet and outlet flow

ρ - Density of the mixture

T_i, T_o - Temperature of inlet and outlet flow

T - Temperature of the mixture

C_{pi}, C_{po} - Specific heat of inlet and outlet fluid

C_p - Specific heat of the mixture

From first principle the balance equation for the CSTR process is given as

$$V \frac{d}{dt} C_A = F C_{AO} - F C_A - k V C_A \quad (4)$$

By rearranging we get the following equation,

$$\frac{d}{dt} C_A + \left(\frac{F}{V} + k\right) C_A = \frac{F}{V} C_{AO} \quad (5)$$

Hence the time constant of the system can be deduced as

$$\tau = \frac{1}{F/V + k}$$

Writing in terms of residence time, we get

$$\tau_R = \frac{V}{F}$$

That is

$$\tau = \frac{1}{\frac{1}{\tau_R} + k} = \frac{\tau_R}{1 + k\tau_R} \quad (6)$$

The rearranged model of the system is then

$$\frac{d}{dt} C_A + \frac{1}{\tau} C_A = \frac{1}{\tau_R} C_{AO} \quad (7)$$

Converting eqn. (4) in transfer function form,

$$G_P = \frac{1}{(1 + \tau_R k)(\tau s + 1)} = \frac{K}{\tau s + 1} \quad (8)$$

Let $\tau_R k = 1$, $\tau = 0.5$ and $K = \frac{1}{1 + \tau_R k}$ we can deduce that,

$$G_P = \frac{0.5}{0.5s + 1} \quad (9)$$

Figure(3) shows the response of the system given in equation (9) which is the reference curve.

From MATLAB System Identification Toolbox, we get

$$G_{P1} = \frac{0.511}{4.6904s + 1} \quad (10)$$

That is $k = 0.511$ and $\tau = 4.6904$

Figure(3) gives the response for the above transfer function. Equation (9) and (10) infers that the estimated model from the system identification toolbox is an inaccurate estimation.

While applying PSO algorithm to same set of input-output data through MATLAB, we get

$$A=1.8111 \text{ and } B=3.6894 \quad (11)$$

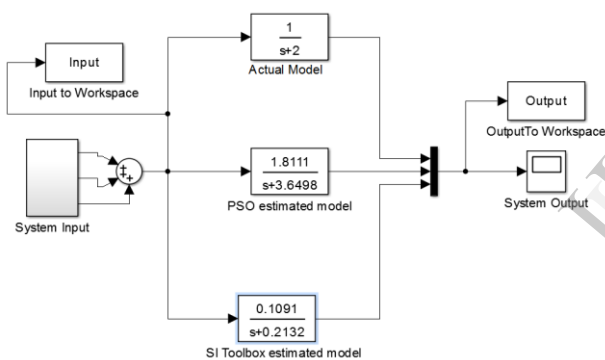
Where $A/B=K$ and $1/B=\tau$

Hence the estimated transfer function would be of the form

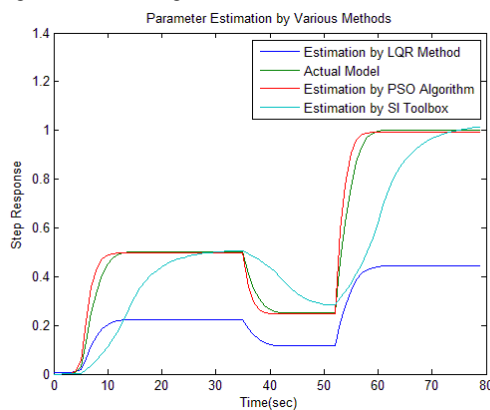
$$G_{P2} = \frac{0.4962}{0.274s+1} \quad (12)$$

Figure(3) depicts the unit step response for the estimated model. Equation (9) and (12) implies that PSO algorithm has produced a better approximation than the other methods.

VI. SIMULATION RESULTS



Figure(2) Block diagram of simulation of estimated models.



Figure(3) Unit step response of actual model and estimated models.

For the given problem of CSTR, the following specifications are considered to compute PSO algorithm^[6].

- Size of the swarm = 56,
- Maximum number of bird steps = 56,
- Dimension(parameters) of the problem = 2
- Correction factor 1= 1.2,
- Correction factor 2 =0.12 and
- Momentum or inertia = 0.9.

Table 1 shows estimated parameters given for different estimation techniques :

Parameter s\Method	Actual Model	SI Toolbox Estimation	LQR Estimation	PSO Estimation
K	0.5	0.5112	0.5110	0.492
τ	0.5	4.6904	4.6901	0.274

Table (1) Comparison of Estimated Parameters

VII. CONCLUSION

There is large gap between the estimated values computed by various methods. The model obtained from PSO is the most accurate one compared to that obtained from other algorithms. So, system identification is found to be more accurate when we use PSO algorithm. Also, this algorithm can be used with more advanced algorithms to produce hybrid ones which may produce a more accurate result.

VIII. REFERENCES

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