mekatronika – Journal of Intelligent Manufacturing & Mechatronics
VOL. 01, ISSUE 02, 66 – 71
DOI: https://doi.org/10.15282/mekatronika.v1i2.4987

ORIGINAL ARTICLE

Simultaneous Model Order and Parameter Estimation (SMOPE) based on Random Asynchronous Particle Swarm Optimization

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ABSTRACT –Simultaneous model order and parameter estimation (SMOPE) is a metaheuristic based system identification method. SMOPE was introduced using particle swarm optimization (PSO). There are several iteration strategies for PSO. The original work on SMOPE is based on synchronous PSO (S-PSO). However, in some works PSO using other iteration strategy is found to give better results. In this work, based on six system identification problems random asynchronous (RA-PSO) based SMOPE is found to have slight advantage over S-PSO.

ARTICLE HISTORY
Received: 2 May 2019
Accepted: 8 July 2019

KEYWORDS
SMOPE
PSO
Random
Asynchronous

Introduction

Simultaneoud model order and parameter estimation (SMOPE) was proposed for solving autoregressive exogenous system identification problem effectively using metaheuristics algorithms [1-2]. The method enabled a system's order and parameters values to be searched simultaneously. This is possible through the way the problem is encoded in the search agents. Even though SMOPE was introduced based on particle swarm optimization (PSO) [1-2], it can easily be adapted to suit other metaheuristic algorithm such as, gravitational search algorithm (GSA) [3-4].

The PSO is a population-based optimization algorithm. The search agents of PSO, known as particles mimics how living organism such as birds and fishes look for food by exploring the search area using their own experience and information from neighborhood as guidance. The search in PSO is done iteratively. PSO's iteration strategy can be classified as synchronous (S-PSO) and asynchronous (APSO) update [5]. S-PSO is more popular approach than A-PSO, where in S-PSO the movement of the whole particles in the swarm is done at once, after their performanceis evaluated. In A-PSO a particle moves as soon as its own performance is evaluated, without the need to wait for others to complete their evaluation. The direction of the movement in A-PSO is made based on whatever information available. This is a more accurate replication of nature.

Random asynchronous PSO (RA-PSO) was introduced in [6]. In the original APSO the particles are evaluated and move according to the particle number. However, in RA-PSO the particle to be evaluated and move is chosen randomly, hence, in an iteration a particle can move more than once or none at all. It is found that RA-PSO is better than A-PSO.

In this work the implementation of SMOPE using RA-PSO is studied and compared with SMOPE based on S-PSO. In several works, implementation of PSO with a particular iteration strategy is found to give a better result compare to other strategy. For example, Wu and Gao had reported that their adaptive inertia weight PSO implemented using asynchronous update has a better performance than the same approach implemented using synchronous update [7]. In [8], A-PSO with discrete crossover is found to perform better than S-PSO with the crossover operator.

However, Engelbrecht in his work concluded that there is no definite winner of S-PSO vs A-PSO but rather it is a function dependent option [5]. The same observation is made in [9].

Therefore, in this work the performance of RA-PSO based SMOPE is compared with the S-PSO based SMOPE. Six ARX system identification problems are used. The results show that RA-PSO on average has a slightly better performance.

Autoregressive Exogenous Model (ARX)

System identification is a task of finding an accurate mathematical model of a control system based on the available input and output data [10]. In [11], the ARX model was introduced by Ljung among many other models for system identification.

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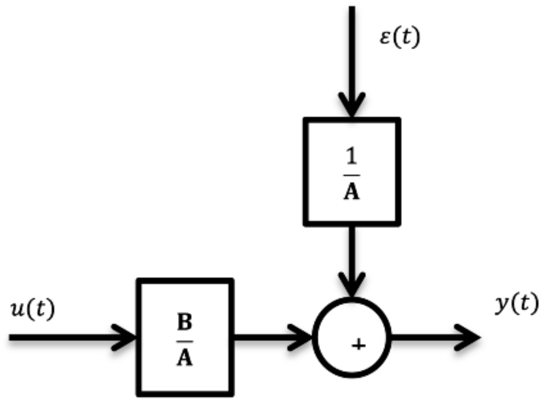

Figure 1. The ARX structure.

The ARX structure is presented in Figure 1. In the figure, $u(t)$ and $y(t)$ represent input and output of the model. The term $\varepsilon(t)$ represents white noise that enters the system as direct error. The mathematical model for ARX is:

Each of the agents in SMOPE represents system order and parameters values. Assuming maximum system order under consideration is D, the agents dimension should be $2D$+1. The first dimension of each agent's represents the system order; n, while dimension 2 to D+1 represents the possible values of poles parameters, $a_1, a_2, \dots, a_{m_a}$ and dimension $D+2$ to $2D + 1$ are reserved for the zeros parameters, $b_1, b_2, \dots, b_{m_b}$. Both m_a and m_b can be lesser than D. If $m_a < D$, then only the values in dimension 2 to m_a+ 1 are used, while the values in dimension $m_a + 2$ to $D + 1$ are ignored. Similarly, if $m_b < D$, then only the values in dimension $D + 2$ to $D + m_b + 1$ are used, while the values in dimension $D + m_b + 2$ to $2D + 1$ are ignored. In this work the maximum order considered is 9 with $m_a \le m_b$.

$$y(t) + a_1 y(t-1) + a_2 y(t-2) + \dots + a_{m_a} y(t - m_a) = b_1 u(t-1) + b_2 u(t-2) + \dots + b_{m_b} y(t - m_b) + \varepsilon(t) \quad (1)$$

where

$$\mathbf{A} = \{a_1, a_2, \dots, a_{m_a}\} \quad (2)$$

$$\mathbf{B} = \{b_1, b_2, \dots, b_{m_b}\} \quad (3)$$

are the tunable parameters. Applying z-transform the transfer function can be written as:

$$G(z) = \frac{Y(z)}{U(z)} = \frac{b_1 z^{-1} + b_2 z^{-2} + \dots + b_m z^{-m}}{1 + a_1 z^{-1} + a_2 z^{-2} + \dots + a_n z^{-n}} \quad (4)$$

The system identification problem is optimized when the best values of the tunable parameters, which are the poles and zeros parameters are found.

SMOPE

In contrast to other system identification approaches, SMOPE find the optimal system order and the parameters values simultaneously. In [1], standard PSO was chosen to search for optimal system order and parameters values.

The key of SMOPE is the encoding of the search agents. Therefore, by adopting similar encoding, SMOPE can easily be applied to other optimization algorithms such as GSA [3-4]. The agent's encoding used in SMOPE is shown in Table 1.

Particle Swarm Optimization

Particle swarm optimization (PSO) is a population based algorithm which has gain popularity due to its simplicity and low computational cost. It has been successfully adapt in various fields, such as robotics [12], power distribution planning [13], and financial planning [14].

Each of the particles in PSO acts as the search agents. The particles has velocity, and position, . The search for optimal solution is conducted in PSO by iteratively evaluating and updating particles performance, velocity and position. The velocity and position are updated according to equation (5) and (6), accordingly. The particles' search direction is influenced by the previous search, their own best performance, *pBest*$_i$, and neighbourhood best, *gBest*. The performance of the particles' can be measured using equation (7). In the equation, $\hat{y}_{(\text{estimation})}$ is the output signal based on the mathematical model found by a particle, whereas y is the actual data and $\hat{y}$ is its mean value.

In this paper, SMOPE is implemented using PSO of two different update strategies, synchronous PSO (S-PSO) and random asynchronous PSO (RA-PSO).

$$v_i(t) = \omega v_i(t-1) + c_1 r_1\big(pBest_i - x_i(t-1)\big) + c_2 r_2\big(gBest - x_i(t-1)\big) \quad (5)$$

$$x_i(t) = v_i(t-1) + x_i(t-1) \quad (6)$$

$$best\ fit = 100\left[1 - \frac{norm(\hat{y}_{estimation} - y)}{norm(y - \hat{y})}\right]\% \quad (7)$$

Synchronous update is the more famous iteration strategy for PSO. In S-PSO, the whole population is updated first before their velocities and positions are updated. Hence, the particles have overview of the whole swarm's performance before the next move is made. The pseudocode for S-PSO is shown in Figure 2. There are two loops per iteration for S-PSO. In the first loop the performance of the whole population is evaluated, whereas the particles velocities and positions are updated in the second loop.

Random asynchronous update is a new iteration strategy for PSO [5]. In RA-PSO, a particle is chosen randomly to be evaluated. Immediately after this particle is evaluated, its velocity and position are updated using the available information. There is no restriction on repetition, hence a particle can be chosen more than once or none at all in an iteration. The chosen particles in RA-PSO are updated based on various neighbourhood information. The pseudocode for RA-PSO is shown in Figure 3. There is only one loop per iteration in RA-PSO. In the loop, first a particle to be evaluated is randomly chosen, then its performance is evaluated, followed by its velocity and position update.

Experiments

Six system identification problems found in database for the identification of system (DaISy) were used. Four of the systems chosen are mechanical systems, which are ball-beam, hair-dryer, wing flutter and robot arm. The data for ball-beam, hairdryer and robot arm systems are obtained from laboratory works while the wing flutter data is obtained from industry. A thermic system namely SISO heating system is also chosen for the experiment. The heating system's output is measured using thermocouple taken from the back of a steel plate. The last experiment is using data from process industry, which is a liquid-saturated steam heat exchanger system.

The first half of the data from each of the systems, is used for training purposed, which is to select the best order and parameters values using SMOPE, while the other half is used for testing.

For example, as shown in Figure 4. The first half of the data for the hair dryer system (in the box) is used for training while the remaining is used to test the quality of the solution found by SMOPE.

Table 1. Agent's encoding.

Dimension	Variable in ARX
1	Order, n
2	a_1
3	a_2
…	…
D+1	a_D
D+2	b_1
D+3	b_2
…	…
2D+1	b_D

```
Random intialization of swarm
do
    for all particles
        evaluate performance
        update pBest and gBest
    end
    for all particles
        update velocity
        update position
    end
while stopping condition is not achieved
```

Figure 2. S-PSO's pseudocode.

```
Random intialization of swarm
do
    for number of particles
        randomly choose a particle
        evaluate performance
        update pBest and gBest
        update velocity
        update position
    end
while stopping condition is not achieved
```

Figure 3. RA-PSO's pseudocode.

The SMOPE method is implemented using both S-PSO and RA-PSO here. The algorithms are using population of 100 particles which are randomly initialized. The algorithms are repeated until either 100% training fitness is achieved or the iteration count exceeds 2000. Each of the experiment is repeated 50 times and the results found are averaged.

Results and Discussions

The results obtained from the experiment are tabulated in Figure 5 and Figure 6 shows the average training fitness in every iteration for each system.

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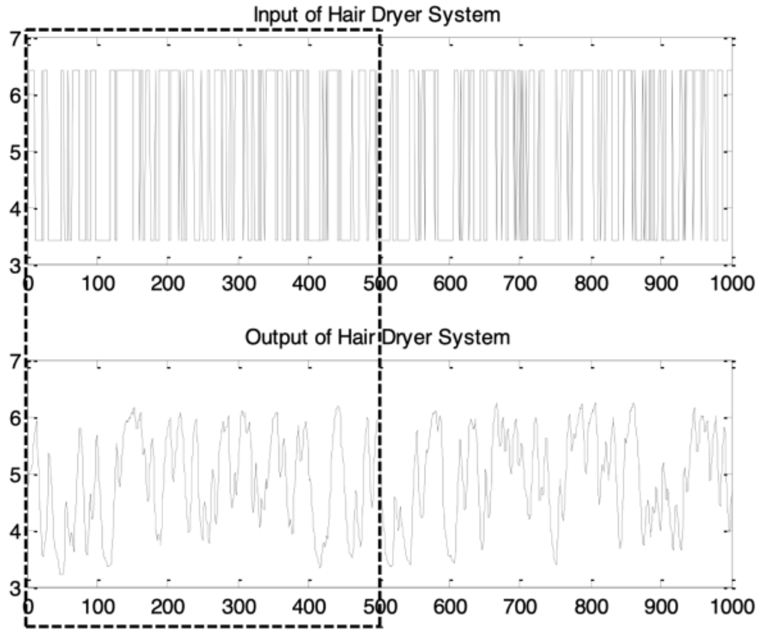

Figure 4. Input and output data of the hair dryer system.

Data Set	Best Fit (Training) (%) Min		Best Fit (Training) (%) Max		Average Best Fit (Training) (%)		STDEV (Training)		Best Fit(Testing) (%) Min		Best Fit(Testing) (%) Max		Average Best Fit (Testing) (%)		STDEV (Testing)	
	S-PSO	RA-PSO	S-PSO	RA-PSO	S-PSO	RA-PSO	S-PSO	RA-PSO	S-PSO	RA-PSO	S-PSO	RA-PSO	S-PSO	RA-PSO	S-PSO	RA-PSO
Heating System	98.6889503	98.5425263	99.050822	99.08616293	98.9185545	98.9465397	0.13134298	0.130077697	97.95234289	97.84396044	98.75276804	98.80992534	98.43944718	98.50297061	0.272288117	0.24904269
Hair Dryer System	87.28354613	87.28354613	95.29308609	95.22151301	90.18634857	90.60407414	2.418449634	2.7124453	86.661686	86.661686	95.23341803	95.21620629	89.93723484	90.34744069	2.561241337	2.884259043
Robot Arm System	90.89111807	90.89111807	97.62446453	98.01874249	95.7206826	95.32097306	1.679574667	2.346756688	90.54979568	90.54979568	97.53494946	97.95395163	95.58480968	95.16320162	1.74418249	2.438258671
Wing Flutter	96.7647563	96.7647563	99.0460994	99.1044069	98.1638475	98.23217188	0.74006768	0.836681164	90.31982512	88.28538273	96.80741887	96.93590385	93.64051679	93.96987304	2.047840589	2.302478218
Ball Beam	96.48437085	96.48437085	97.46363029	97.46799711	97.20772236	97.19802756	0.184859727	0.192925859	96.57586006	96.57586007	97.82374866	97.81936721	97.47986053	97.46523921	0.241399928	0.253951298
Exchanger System	80.2564027	80.2564027	81.0192168	80.9348651	80.6598087	80.672473	0.29214031	0.29528128	49.41739614	49.41739615	50.41210458	50.41421039	50.00940316	50.03078219	0.434425592	0.435529237

Figure 5. Performance of S-PSO based SMOPE vs RA-PSO based SMOPE.

On average RA-PSO has a slight advantage over the original implementation which is based on S-PSO. Out of the six systems used, RA-PSO performs better in four systems, which are the heating system, exchanger system, hair dryer system and wing flutter system. RA-PSO has a better performance for these systems in training phase as well as in the testing stage. However, the differences between the two algorithms are marginal.

The marginal difference can be seen in Figure 5. It can be seen that in all iteration the fitness of S-PSO based SMOPE and RA-PSO based SMOPE is close to each other. The mathematical models for each system found by both algorithms are presented in Figure 7. Both algorithms found their own model with their own parameters values and system order.

Conclusion

SMOPE is a metaheuristic based system identification method. The method is able to determine the system order and the parameters simultaneously. This work investigates the difference between S-PSO based and RA-PSO based SMOPE. The implementation of SMOPE using RA-PSO is found to have a slight advantage over its implementation using S-PSO.

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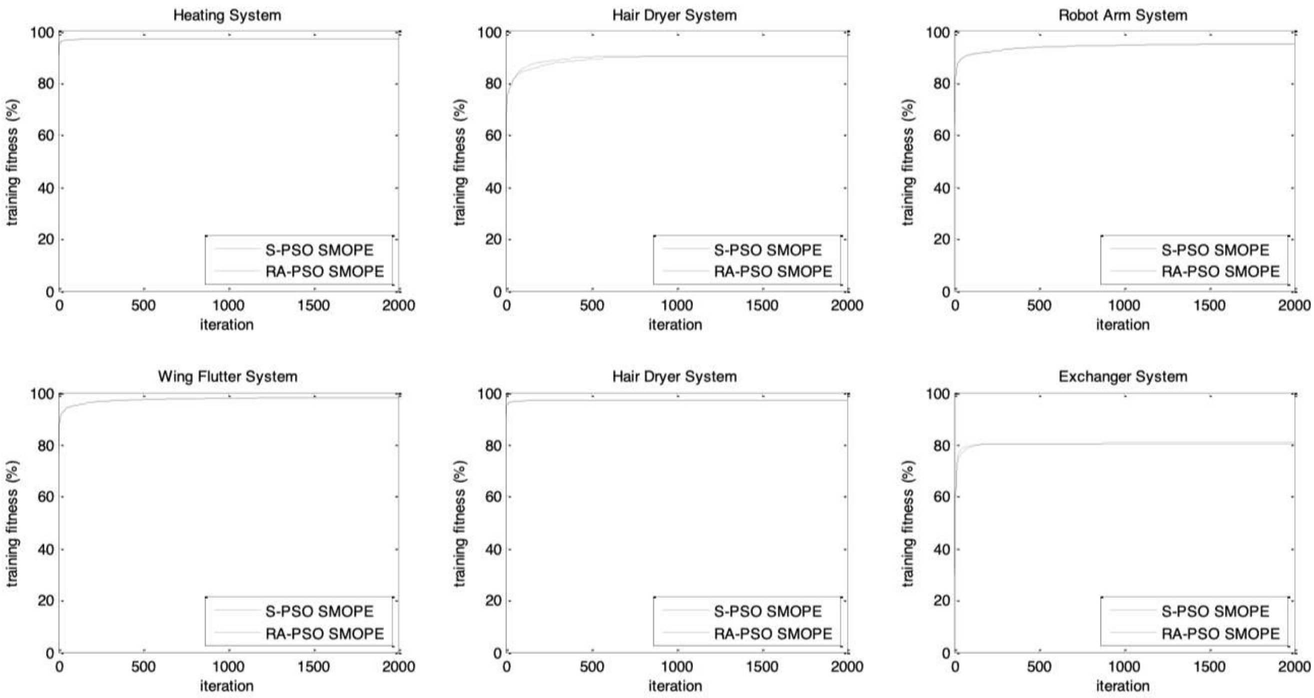

Figure 6. Convergence curves.

	S-PSO based SMOPE	RA-PSO based SMOPE-PSO
Heating System	$G_8(Z) = \frac{1.1728E-01Z^{-1} + 1.2558E-01Z^{-2}}{1 - 1.5447E+00Z^{-1} + 5.1517E-01Z^{-2} + 4.0880E-02Z^{-3}}$	$G_7(Z) = \frac{2.0558E-01\,Z^{-1}}{1 - 1.6480E+00\,Z^{-1} + 4.2510E-01Z^{-2} + 4.7193E-01Z^{-3} - 2.3945E-01Z^{-4}}$
Hair Dryer System	$G_{10}(Z) = \frac{1.9353E-03Z^{-1} + 3.4780E-03Z^{-2} + 6.3246E-02Z^{-3} + -2.4032E+00Z^{-4}}{1 - 1.0969E+00Z^{-1} + 4.9053E-02Z^{-2} + 2.4258E-01Z^{-3} - 6.5639E-02Z^{-4}}$	$G_{10}(Z) = \frac{-4.3221E-04\,Z^{-1} + 5.0368E-03\,Z^{-2} + 6.3328E-02\,Z^{-3} + 5.5303E-02\,Z^{-4}}{1 - 1.1112E+00\,Z^{-1} + 7.0820E-02\,Z^{-2} + 2.3274E-01\,Z^{-3} - 6.5128E-02\,Z^{-4}}$
Robot Arm System	$G_9(Z) = \frac{-6.2515E-02Z^{-1} + 7.3661E-02Z^{-2} - 2.6292E-02Z^{-2}}{1 - 2.8196E+00Z^{-1} + 3.6585E+00Z^{-2} - 2.3624E+00Z^{-3} + 6.7654E-01Z^{-4}}$	$G_{28}(Z) = \frac{-5.8551E-01\,Z^{-1} + 1.3019E+00\,Z^{-2} - 1.2507E+00Z^{-3} + 6.2992E-01\,Z^{-4} + 2.3527E-02\,Z^{-5} - 5.4968E-02\,Z^{-6} - 1.1418E-0}{1 - 1.2279E+00\,Z^{-1} + -2.9497E-01\,Z^{-2} + 1.0180E+00Z^{-3} + 4.5509E-01Z^{-4} - 9.4178E-01\,Z^{-5} - 1.5290E-01\,Z^{-6} + 5.6338E-0}$
Wing Flutter	$G_4(Z) = \frac{-3.3964E-02Z^{-1}}{1 - 2.6113E+00Z^{-1} + 2.4575E+00Z^{-2} - 8.3518E-01Z^{-3}}$	$G_{16}(Z) = \frac{-4.6148E-02\,Z^{-1}}{1 - 2.2871E+00\,Z^{-1} + 1.4704E+00\,Z^{-2} + 3.3797E-01\,Z^{-3} - 5.9775E-01\,Z^{-4} + 5.0341E-02\,Z^{-5} + 4.1748E-02Z^{-6}}$
Ball Beam	$G_{24}(Z) = \frac{-2.7357E-01Z^{-1} + 1.5260E-01Z^{-2} + 2.9661E-01Z^{-3}}{1 - 9.1080E-01Z^{-1} - 2.8977E-01Z^{-2} + 6.4964E-02Z^{-3} - 1.0381E-01Z^{-4} + 2.8406E-02Z^{-5} + -2.0432E-02Z^{-6} + 2.2931E-01Z^{-7}}$	$G_{25}(Z) = \frac{-1.9259E-01\,Z^{-1} + 1.3219E-01\,Z^{-2} + 1.2913E-01\,Z^{-3} + 9.9303E-02\,Z^{-4}}{1 - 9.9073E-01\,Z^{-1} - 2.1849E-01\,Z^{-2} + 1.0525E-01Z^{-3} - 1.3891E-01\,Z^{-4} + 5.4615E-02\,Z^{-5} - 1.2018E-02\,Z^{-6} + 1.9815E-01}$
Exchanger System	$G_2(Z) = \frac{2.2076E-01Z^{-1}}{1 - 1.2569E+00Z^{-1} + 2.5761E-01Z^{-2}}$	$G_2(Z) = \frac{2.3113E-01\,Z^{-1}}{1 - 1.2661E+00\,Z^{-1} + 2.6692E-01\,Z^{-2}}$

Figure 7. Mathematical models.

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