Frequency-weighted Model Reduction Using Firefly Algorithm

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***Abstract*—This paper deals with a frequency-weighted model reduction for single-input, single-output systems combining the linear least-squares (LS) method with firefly algorithm (FA). The reduced-order model is determined by minimizing the integral of the magnitude squared of the frequency-weighted transfer function error. The denominator parameters and time delay of the reduced-order model are represented by the positions of the fireflies and searched for by the FA, while the numerator parameters are estimated by the linear LS method for each candidate of the denominator parameters and time delay. All the best parameters and the time delay of the reduced-order model are obtained through the search by the fireflies. Simulation results show that the accuracy of the proposed method is comparable to that of the genetic algorithm (GA)-based model reduction algorithm, with smaller computational burden.**

***Index Terms*—model reduction, frequency-weighting, separable least-squares, firefly algorithm**

I. INTRODUCTION

Since many practical systems are of high-order, the problem of approximating high-order systems by low-order models is one of the important problems in system theory. The use of a good approximated low-order model reduces the computational burden to implement system analyses, simulations and control designs. Model reduction algorithms have been developed using a number of approaches [1]-[12].One of the popular approaches is the L_2 optimal modelreduction. In this approach, the reduced-order model is generally determinedso that a quadratic cost, i.e., the integral of the magnitude squared of the transfer function errorbetween the original system and the reduced-order model, is minimized. The minimization of this cost function is a nonlinear problem with respect to the denominator parameters and the time delay of the reduced-order model. Therefore, we have to solve a very complicated nonlinear optimization problem for L_2 optimal model reduction. For this problem, one of the authors proposed the hybrid model reduction algorithms [10]-[12] combining the linear least-squares (LS) method with the genetic algorithm (GA) [13], or artificial bee colony (ABC) algorithm [14]. However, the GA has many setting parameters and requires a complicated coding technique and genetic operations. The ABC algorithm has very few setting parameters, but the structure is slightly complicatedowing to the search of three types of bee.

To improve the efficiency of model reduction, in this paper, we propose a novelL_2model reduction algorithm for single-input, single-outputcontinuous-time systems combining the linear LS method with the firefly algorithm (FA). The FA is an optimization technique inspired by an intelligent behavior of firefly swarms [15]. In the FA, for any two flashing fireflies, the less brighter firefly moves toward the brighter one according to the attractiveness. The attractiveness is proportional to the light intensity observed by the partner and monotonically decreases as the distance between two fire flies increases, owing to the inverse square law and the absorption property of light. The FA consists of only the basic arithmetic operations and does not require complicated coding and genetic operations such as crossovers and mutations of the GA. Moreover, the performance and computational cost of the FA are shown to be better than those of other population-based algorithmssuch as the GA and the particle swarm optimization [15], [16]. These advantages suggest that the use of the FA increases efficiency without deterioration of approximation accuracy for model reduction.

Note that if the denominator parameters and time delay of the reduced-order model are fixed *a priori*, the determination of the numerator parameters becomes a linear problem, and they are easily obtained by the linear LS method. Therefore, we propose a separable LS approach combining the linear LS method with the FA to determine reduced-order models. The denominator parameters and time delay of the reduced-order model are represented by the positions of the fireflies and searched for by the FA, while the numerator parameters are estimated by the linear LS method for each candidate of the denominator parameters and time delay. The light intensities (fitness values) of the fireflies are evaluated as the inverse of the integral of the magnitude squared of the frequency-weighted transfer function errors between the original system and the candidates of the reduced-order model. All the best parameters and the time delay of the reduced-order model are obtained through searching by the fireflies.

This paper is organized as follows. In Section II, the problem is formulated. In Section III, the numerator parameters of the reduced-order model are representedas a function of the denominator parameters and time delay.

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Then the model reduction algorithm is given by a separable LS approach that combines the linear LS method with the FA. In Section IV, simulation results are shown to illustrate the effectiveness of the proposed model reduction method. Finally, some conclusions are given in Section V.

II. Statement of the Problem

Consider an nth-order single-input, single-output time delay system with the transfer function:

$$G(s) = \frac{\beta_1 s^{m-1} + \beta_2 s^{m-2} + \cdots + \beta_m}{s^n + \alpha_1 s^{n-1} + \alpha_2 s^{n-2} + \cdots + \alpha_n} \exp(-\tau s) \quad (1)$$

where the rational part is stable and strictly proper.

Let the ℓth-order reduced model with the time delay be given by

$$\tilde{G}(s) = \frac{d_1 s^{k-1} + d_2 s^{k-2} + \cdots + d_k}{\prod_{i=1}^{[\ell/2]}(s^2 + a_i s + b_i)} \exp(-Ts) \quad (\ell\text{: even})$$
$$= \frac{d_1 s^{k-1} + d_2 s^{k-2} + \cdots + d_k}{\left\{\prod_{i=1}^{[\ell/2]}(s^2 + a_i s + b_i)\right\}(s + c)} \exp(-Ts) \quad (\ell\text{: odd}) \quad (2)$$

where $\ell < n$ and $[\cdot]$ denotes Gauss's symbol. The rational parts of (2) are also strictly proper. Note that the form of the denominator in (2) enables us to express all possible patterns of the poles and guarantees the stability of the reduced-order model when all denominator parameters $\{a_i\}$, $\{b_i\}$ and c are positive. Many real systems have inherently pure time delays, and systems of multiple first-order lags in a cascade also perform as if they are time delay systems [7]. When such systems are approximated by only rational transfer functions, the order of the reduced model has to be high for good approximation. If an additional time delay is introduced into the reduced-order model, the approximation might be greatly improved with fewer parameters of the rational part.

Our goal is to determine the parameters $\{a_i\}$, $\{b_i\}$, c, $\{d_i\}$ and the time delay T of the stable reduced-order model so that the integral of the magnitude squared of the frequency-weighted transfer function error:

$$J = \int_{-\infty}^{+\infty} \left| \left\{ G(j\omega) - \tilde{G}(j\omega) \right\} W(j\omega) \right|^2 d\omega \quad (3)$$

is minimized. Here $W(j\omega)$ is a frequency-weighting function, which is introduced to obtain a better approximation over a prespecified frequency range such as near resonances and operating frequencies.

III. Model Reduction Algorithm

A. Representation of Numerator Parameters by LS Method

In this section, we show that the numerator parameters of the reduced-order model are represented as a function of the denominator parameters and time delay. In the following, only the odd case of (2) is considered, because the even case of (2) can be treated in the same manner.

The reduced-order model (2) can be rewritten as

$$\tilde{G}(j\omega) = \boldsymbol{z}^T(j\omega, \boldsymbol{X})\boldsymbol{\theta}$$
$$\boldsymbol{z}^T(j\omega, \boldsymbol{X}) = \frac{\left[(j\omega)^{k-1} (j\omega)^{k-2} \cdots j\omega \quad 1\right]}{\prod_{i=1}^{[\ell/2]}\{(j\omega)^2 + a_i(j\omega) + b_i\}\{(j\omega) + c\}} \times \exp(-j\omega T) \quad (4)$$

where

$$\boldsymbol{X} = \left[a_1 b_1 \cdots a_{[\ell/2]}\, b_{[\ell/2]}\, c\, T\right]^T$$
$$\boldsymbol{\theta} = [d_1\, d_2\, \cdots\, d_{k-1}\, d_k]^T \quad (5)$$

$\boldsymbol{X}$ consists of the denominator parameters and time delay, and $\boldsymbol{\theta}$ consists of the numerator parameters of the reduced-order model. Then the cost function (3) is given using (4) as follows:

$$J(\boldsymbol{X}, \boldsymbol{\theta}) = \int_{-\infty}^{+\infty} |\{G(j\omega) - \boldsymbol{z}^T(j\omega, \boldsymbol{X})\boldsymbol{\theta}\}W(j\omega)|^2 d\omega$$
$$= \int_{-\infty}^{+\infty} ([W(j\omega)G(j\omega)]_R - [W(j\omega)\boldsymbol{z}^T(j\omega, \boldsymbol{X})]_R \boldsymbol{\theta})^2 + ([W(j\omega)G(j\omega)]_I - [W(j\omega)\boldsymbol{z}^T(j\omega, \boldsymbol{X})]_I \boldsymbol{\theta})^2 d\omega \quad (6)$$

where $[\cdot]_R$ and $[\cdot]_I$ denote the real and imaginary parts of the complex number, respectively. Thus, applying the linear LS method to (6), the numerator parameter vector $\boldsymbol{\theta}$ is obtained as a function of $\boldsymbol{X}$:

$$\boldsymbol{\theta}(\boldsymbol{X}) = \left[\int_{-\infty}^{+\infty} [W(j\omega)\boldsymbol{z}(j\omega, \boldsymbol{X})]_R [W(j\omega)\boldsymbol{z}^T(j\omega, \boldsymbol{X})]_R + [W(j\omega)\boldsymbol{z}(j\omega, \boldsymbol{X})]_I [W(j\omega)\boldsymbol{z}^T(j\omega, \boldsymbol{X})]_I d\omega \right]^{-1} \times \left[\int_{-\infty}^{+\infty} [W(j\omega)\boldsymbol{z}(j\omega, \boldsymbol{X})]_R [W(j\omega)G(j\omega)]_R + [W(j\omega)\boldsymbol{z}(j\omega, \boldsymbol{X})]_I [W(j\omega)G(j\omega)]_I d\omega \right] \quad (7)$$

B. Model Reduction by FA

As the cost function J of (3) or (6) generally has multiple local minima, this model reduction becomes a nonlinear optimization problem. However, we can separate the linear optimization part and the nonlinear optimization part for this optimization problem. Note that if the candidates of the vector $\boldsymbol{X}$, which consists of the denominator parameters and time delay, are given, the numerator parameter vector $\boldsymbol{\theta}$ can be estimated by the linear LS method as shown in (7). Therefore, in this paper we present the model reduction algorithm by a separable LS approach combining the linear LS method with the FA. The candidates of $\boldsymbol{X}$ are represented by the positions of the fireflies and searched for by the FA, where the candidates of the numerator parameter vector $\boldsymbol{\theta}$ are estimated by the linear LS method.

Of course, it is possible to optimize both $\boldsymbol{X}$ and $\boldsymbol{\theta}$ directly using only the FA. However, such a naive method makes the FA computationally demandingbecause the dimension of the search space increases. The proposed separable LS approach is more efficient in that it reduces the dimension of the search space by about half.

The proposed model reduction algorithm is described as follows:

Step 1: Initialization

Generate an initial population of$Q$fireflies with random positions $\boldsymbol{X}_{[i]}$ $(i = 1,2,\cdots,Q)$.

Set the iteration counter$l$to 0.

Step 2: Estimation of numerator parameter$\boldsymbol{\theta}$

Calculate the numerator parameter vector $\boldsymbol{\theta}_{[i]}$from (7) by the linear LS methodfor $\boldsymbol{X}_{[i]}$ $(i = 1,2,\cdots,Q)$ .In practice, the integral in(7) is carried out by a numerical integration methodsuch as the trapezoidal rule with a reasonable range $[0, \omega_f]$.

Step 3: Light intensity calculation

Calculate the light intensity $I_i$of each firefly from(8):

$$I_i(\boldsymbol{X}_{[i]}, \boldsymbol{\theta}_{[i]}) = \frac{1}{\int_0^{\omega_f} \left|\{G(j\omega) - \boldsymbol{z}^T(j\omega, \boldsymbol{X}_{[i]})\boldsymbol{\theta}_{[i]}\}W(j\omega)\right|^2 d\omega} \tag{8}$$

where the range of the integral is set to$[0, \omega_f]$ as in *step 2*.Note that the light intensity is the inverse of the cost function (6), i.e., maximizing the light intensity means minimizing the cost function.

Step 4: Sorting of the fireflies

Sort the fireflies in ascending order of their light intensities and find the current best position:

$$\boldsymbol{X}_{best}^{l} = \boldsymbol{X}_{[Q]} \tag{9}$$

Step 5: Movement of the fireflies

If $I_i(\boldsymbol{X}_{[i]}, \boldsymbol{\theta}_{[i]}) < I_j(\boldsymbol{X}_{[j]}, \boldsymbol{\theta}_{[j]})$, move a firefly i at position$\boldsymbol{X}_{[i]}$ toward a brighter firefly$j$ atposition $\boldsymbol{X}_{[j]}$ by

$$\boldsymbol{X}_{[i]} = \boldsymbol{X}_{[i]} + \beta_0 \exp(-\gamma r_{ij}^2)(\boldsymbol{X}_{[j]} - \boldsymbol{X}_{[i]}) + \alpha_l \cdot rand() \tag{10}$$

where $r_{ij}$is the Euclidean distance between $\boldsymbol{X}_{[i]}$and$\boldsymbol{X}_{[j]}$, $\beta_0$isthe attractivenessat $r_{ij} = 0$, $\gamma$is themedia absorption coefficient, α_l is the randomization parameter, and $rand()$ is uniformly distributed random number with amplitude in the range $[-0.5, 0.5]$. $\beta = \beta_0 \exp(-\gamma r_{ij}^2)$is the attractiveness between the fireflies$i$ and j.

Step 6: Repetition

Set the iteration counter to $l = l + 1$ and go to *step 2* until the prespecified iteration numberl_{max}.

Finally at the termination of this algorithm when$l = l_{max}$, the suboptimal $\widehat{\boldsymbol{X}}$ and the corresponding $\widehat{\boldsymbol{\theta}}$ are determined by the best position $\boldsymbol{X}_{best}^{l_{max}}$of the firefly.

IV. Numerical Simulations

Consider the fifth-order nonminimal phase system with time delaydescribed by the following transfer function [9]:

$$G(s) = \frac{(s+1)(s-1)(s+10)}{(s+2)^3(s+3)(s+4)} \exp(-0.5s) \tag{11}$$

The setting parameters of the FA are chosen as follows:

firefly size: $Q = \ell \times 200$

attractiveness at $r_{ij} = 0$: $\beta_0 = 1.0$

media absorption coefficient: $\gamma = 1.0$

randomization parameter:

$\alpha_l = 1.0 \times 0.97^l$(for denominator parameters)

$\alpha_l = 0.1 \times 0.97^l$(fortime delay)

maximum iteration number:$l_{max} = 100$

The first-order and second-order reduced models with the time delay obtained by the proposed algorithm are

$$\tilde{G}_1(s) = \frac{-0.17266}{s + 1.0188} \exp(-1.3770s) \tag{12}$$

$$\tilde{G}_2(s) = \frac{0.22652s - 0.24951}{s^2 + 1.8158s + 2.5683} \exp(-0.64583s) \tag{13}$$

where the frequency-weighting function $W(s) = 1$ (unity weighting).Note that in practice the use of the first-order reduced model is not realistic if the model reduction is carried out for a control design,because the high-order system (11) has resonance characteristics.

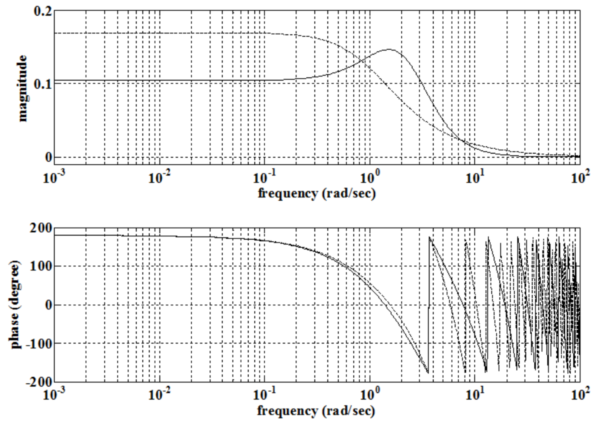

Figure 1. Bode plots of the original system and reduced-order model $(-G(s), \cdots \tilde{G}_1(s))$.

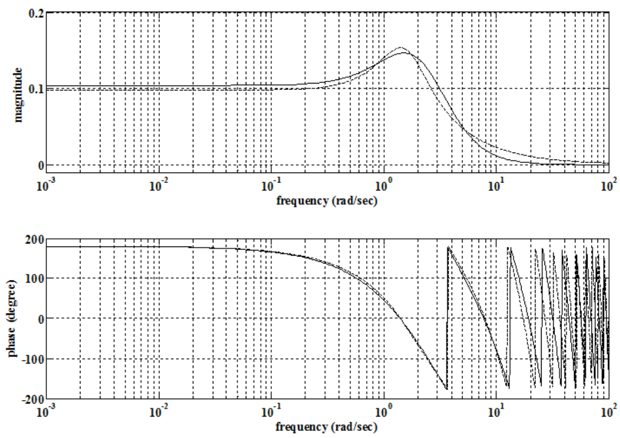

Figure 2. Bode plots of the original system and reduced-order model $(-G(s), \cdots \tilde{G}_2(s))$.

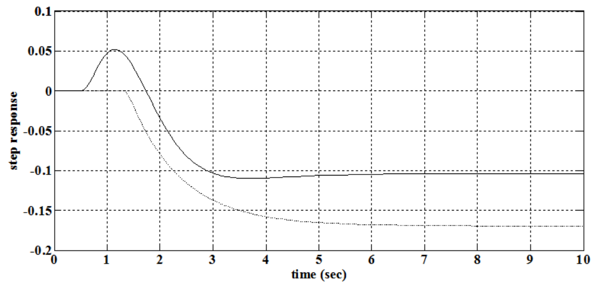

Figure 3.Step responses of the original system and reduced-order model ($-G(s), \cdots \tilde{G}_1(s)$).

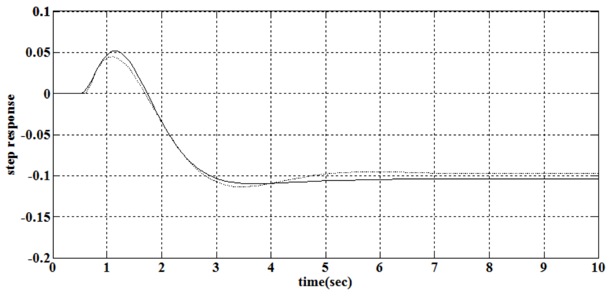

Figure 4.Step responses of the original system and reduced-order model ($-G(s), \cdots \tilde{G}_2(s)$).

The Bode plots of the original system $G(s)$ and the reduced-ordermodels $\tilde{G}_1(s)$ and $\tilde{G}_2(s)$ are shown in Fig. 1 and Fig. 2. The step responses of $\tilde{G}_1(s)$ and $\tilde{G}_2(s)$are also respectively shown in Fig. 3 and Fig. 4, which are compared with those of the frequency-weighted reduced-order models later. The first-order and second-order reduced models have quite large approximation errors at low frequencies. Since many practical systems operate in low-frequency ranges, we proceed to the frequency-weighted model reduction to obtain a better approximation at low frequencies. The following frequency-weighting function with low-pass characteristic

$$W(s) = \begin{cases} \dfrac{1}{(s+0.1)^2} & (\ell = 1) \\ \dfrac{1}{(s+3)^2} & (\ell = 2) \end{cases} \tag{14}$$

is introduced. The first-order and second-order frequency-weighted reduced models are obtained as follows:

$$\tilde{G}_{1w}(s) = \frac{-1.0451}{s+9.9868}\exp(-2.3442s) \tag{15}$$

$$\tilde{G}_{2w}(s) = \frac{0.30591s - 0.31891}{s^2 + 2.4681s + 3.0437}\exp(-0.69461s) \tag{16}$$

The Bode plots of the original system $G(s)$and the frequency-weighted reduced-order models $\tilde{G}_{1w}(s)$ and $\tilde{G}_{2w}(s)$ are shown in Fig. 5 and Fig. 6, and their step responses are shown in Fig. 7 and Fig. 8, respectively. Although it is difficult to judge which is better, the step response of $\tilde{G}_1(s)$ or the step response $\tilde{G}_{1w}(s)$,the approximation errors of the frequency-weighted reduced models$\tilde{G}_{1w}(s)$ and $\tilde{G}_{2w}(s)$are smaller than those of the unity-weighted reduced-order models $\tilde{G}_1(s)$ and $\tilde{G}_2(s)$, respectively, at low frequencies.Moreover, the steady-state errors of the step responses of $\tilde{G}_{1w}(s)$ and $\tilde{G}_{2w}(s)$are considerably improvedbecause the gain errors at the frequency $\omega = 0$become smaller owing to the use of the frequency-weightingfunction with low-passcharacteristics.Therefore, the proposed method can successfully carry out the frequency-weighted model reduction. In control design, the reduction of the steady-state error is one of the important themes. For this purpose, it is effective to choose the frequency-weighting function $W(s)$ so that it has low-pass characteristics.

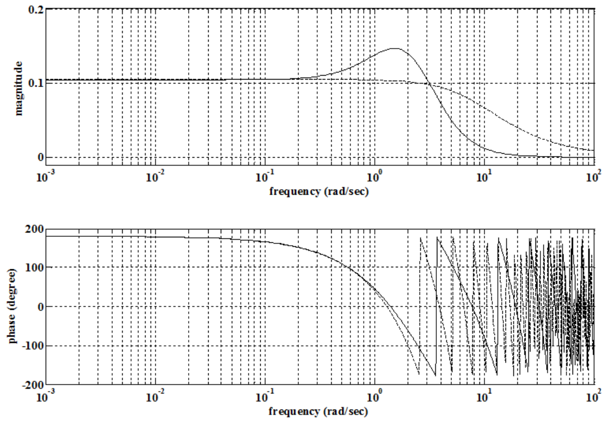

Figure 5. Bode plots of the original system and frequency-weighted reduced-order model ($-G(s), \cdots \tilde{G}_{1w}(s)$).

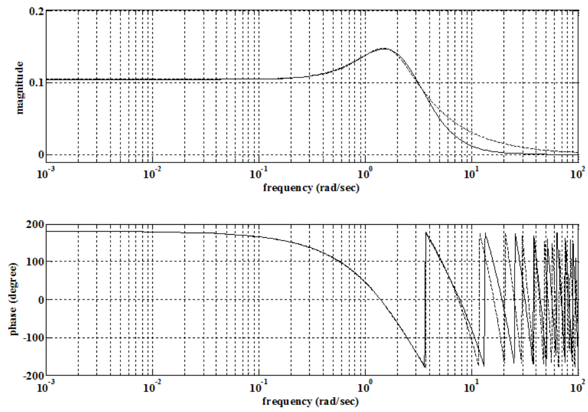

Figure 6. Bode plots of the original system and frequency-weighted reduced-order model ($-G(s), \cdots \tilde{G}_{2w}(s)$).

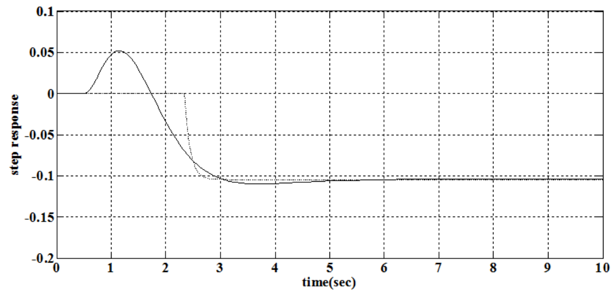

Figure 7.Step responses of the original system and frequency-weighted reduced-order model ($-G(s), \cdots \tilde{G}_{1w}(s)$).

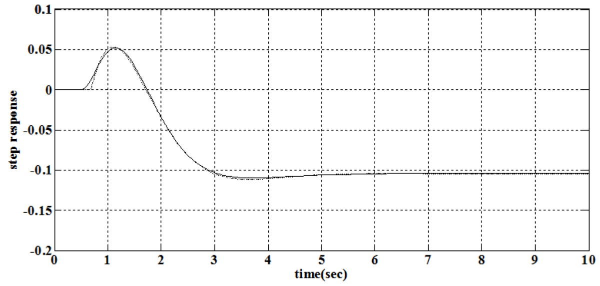

Figure 8.Step responses of the original system and frequency-weighted reduced-order model ($-G(s), \cdots \tilde{G}_{2w}(s)$).

To carry out a comparison with the GA-based model reduction method [10], [11], Monte Carlo simulations with20 experiments are implemented, where 20 setups of the initial population are generated for both the FA and the GA. The population size of the GA is set to be $M = \ell \times 200$ so that the number of fitness value calculations of the GA is the same as that of the FA.The integrals of the magnitude squared of the transfer function errors in the case of the unity weighting are shown in Table I. The transfer function errors obtained by the proposed method are almost the same as those obtained by the GA-based method. Table II shows the computational times of the proposed method and the GA-based method (CPU: Intel(R) Core 2 Duo E8600 3.33GHz). We can confirm that the proposed method can reduce the computational burden without deteriorate of approximation accuracy.

TABLE I. INTEGRALS OF THE MAGNITUDE SQUARED OF THE TRANSFER FUNCTION ERRORS

model	Proposed method	GA-based method
$\tilde{G}_1(s)$	2.119e-2	2.120e-2
$\tilde{G}_2(s)$	2.880e-3	2.889e-3

TABLE II. COMPUTATIONAL TIMES

model	Proposed method	GA-based method
$\tilde{G}_1(s)$	525.5 (s)	536.5 (s)
$\tilde{G}_2(s)$	1409.4 (s)	1941.6 (s)

V. CONCLUSIONS

In this paper, a novel method of frequency-weighted model reduction with a time delay for single-input, single-output continuous-time systems has been presented using a separable LS approach. The linear LS method and the FA are efficiently combined to determine the parameters of the rational part and the time delay of the reduced-ordermodel. The denominator parameters and time delay are represented by the positions of the fireflies and searched for by the FA, where the candidates of the numerator parameters are estimated by the linear LS method. Simulation results show that the reduced-order models obtained by the proposed method yield good approximations to the original system for bothunity-weighted and frequency-weighted model reduction. Simulation results also show that the accuracy of the proposed methodis comparable to that of the GA-based model reduction method, with smaller computational burden.

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