Research Article

Using an Improved Artificial Bee Colony Algorithm for Parameter Estimation of a Dynamic Grain Flow Model

He Wang¹, Hongbin Liang¹ and Lei Gao²

¹School of Mechanical Engineering and Automation, University of Science and Technology Liaoning, Anshan 114051, China

²Department of Information Service and Intelligent Control, Shenyang Institute of Automation, Chinese Academy of Sciences, Shenyang 110016, China

Correspondence should be addressed to He Wang; wanghe@ustl.edu.cn

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An effective method is proposed to estimate the parameters of a dynamic grain flow model (DGFM). To this end, an improved artificial bee colony (IABC) algorithm is used to estimate unknown parameters of DGFM with minimizing a given objective function. A comparative study of the performance of the IABC algorithm and the other ABC variants on several benchmark functions is carried out, and the results present a significant improvement in performance over the other ABC variants. The practical application performance of the IABC is compared to that of the nonlinear least squares (NLS), particle swarm optimization (PSO), and genetic algorithm (GA). The compared results demonstrate that IABC algorithm is more accurate and effective for the parameter estimation of DGFM than the other algorithms.

1. Introduction

Grain flow sensor is an important part of yield monitoring system in precision agriculture. There are mainly four types of grain flow sensor: impact-type [1], ray-type [2], volume-type [3], and weight-type [4]. Most commercial yield monitoring systems rely on impact-type for security, reliability, and simple structure. Impact-type measures the grain force exerted on the sensing device usually at the exit of the clean grain elevator, shown in Figure 1. The measured force is related to the grain flow.

Grain flow model is used to characterize the relationship between the grain flow and the impact force, which contains linear models and nonlinear models. Linear models have been utilized due to being easy for model building [5–8]. The results of the experiment, by contrast, denote a strongly nonlinear relation between the grain flow and the impact force at larger grain flow [9], so nonlinear models have been proposed for grain flow sensor to estimate a wide range of grain flow [10, 11] and are gradually employed for mass flow sensors to minimize the effects of changes in material properties [12, 13]. At this time, nonlinear regression methods

are used to estimate parameter of nonlinear models with minimizing a given objective function [11, 14, 15]. But these methods have disadvantages of low convergence precision and slow convergence rate.

Recently, many artificial intelligent techniques have emerged as useful tool to solve complex problems, and these techniques have been utilized to parameter estimation of nonlinear models. In [16], application of an ant colony optimization (ACO) algorithm on estimation of the ultrasonic echo parameters shows the feasibility of ACO algorithm. The artificial bee colony algorithm (ABC) is used to search the appropriate combinations of the driving waveform parameters [17]. The particle swarm optimization (PSO) to determine the unknown photovoltaic (PV) model parameters was proposed by Soon and Low [18]. A multiobjective genetic algorithm (MOGA) is utilized to determine reliable estimates of the physical parameters of a complex robotic arm which are not known in advance [19]. Artificial intelligence techniques are superior to the traditional methods and have the obvious advantages of solving the global optimization problem with high precision and short time. However, artificial intelligent techniques still have some challenges to overcome, such

FIGURE 1: Work schematic of impact grain flow sensor.

as problem of falling into local optimums and problem of convergence rate.

ABC has been proven to be a powerful and efficient tool for real-world optimization problems [20–22]. In order to efficiently and accurately estimate parameters of nonlinear grain flow models, this paper is to develop an improved artificial bee colony (IABC) algorithm and employ IABC to estimate parameter of DGFM and compare the results with other methods. Therefore, we have redefined new food sources in original ABC algorithm to obtain a new variant version of this algorithm which, compared to the other ABC variants, is highly effective for improved search performance.

The paper is organized as follows. In Section 2, related works about DGFM and ABC algorithm are introduced. In Section 3, IABC algorithm is detailed. In Section 4, IABC algorithm is compared with the other ABC variants on benchmark functions. In Section 5, IABC algorithm is used to estimate parameters of DGFM and comparison results are presented. Conclusions are made in Section 6.

2. Relate Works

2.1. DGFM. As mentioned above, it is a trend to model grain flow using nonlinear models. DGFM is proposed to give an accurate estimation of grain flow [23]. DGFM is classified into four stages: the filling stage, the settling stage, the release stage, and the flight stage.

2.1.1. Filling Stage. Total grain mass on a paddle is obtained as follows:

$$M = \dot{m} \int P(t) dt = \dot{m} \frac{d}{V}, \quad (1)$$

where M is total grain mass on a paddle, $\dot{m}$ is the mass flow, $P(t)$ is the coefficient of opening of the auger at time t , d is the distance between two paddles, and V is the linear velocity of the paddles.

2.1.2. Settling Stage. $h(\psi)$ is the distance between the sprocket center and inner boundary of the grains at any angle. ψ is calculated as follows:

$$h(\psi) = l \left(\frac{l}{h_0} \cos \psi + \left(1 - \frac{l}{h_0} \cos \psi_f \right) \frac{\sin \psi}{\sin \psi_f} \right)^{-1}, \quad (2)$$

where l is length of the paddle and ψ_f is the maximal angle achieved by the grain distribution. Specifically, $h(0) = h_0$, $h(\psi_f) = l$, ψ_f and h_0 can be obtained from (3) and (4), respectively.

$$\psi_f = \frac{h_f(l - h_0)}{l} \quad (3)$$

$$\frac{M}{\eta w l^2} = \frac{h_f(l - h_0) - h_0 \sin(h_f((l - h_0)/l))}{2l}, \quad (4)$$

where h_f is the grain shape coefficient to be estimated, η is the density of the grain, and w is the width of the paddle.

2.1.3. Release Stage. Horizontal velocity and vertical velocity at the end of the release stage are given by

$$\begin{aligned} v_x &= l\Omega (\tilde{\rho}'(\tau_d) \cos(\theta_d) - \sin(\theta_d)) \\ v_y &= l\Omega (\tilde{\rho}'(\tau_d) \cos(\theta_d) + \sin(\theta_d)) \\ \tilde{\rho}'(\tau_d) &= \frac{1}{2} \left(\tilde{\rho}_0 - \frac{\tilde{\rho}_0 \mu}{\sqrt{1 + \mu^2}} \right) \\ &\quad \cdot e^{(-\mu - \sqrt{1 + \mu^2})\tau_d} (-\mu - \sqrt{1 + \mu^2}) \\ &\quad + \frac{1}{2} \left(\tilde{\rho}_0 + \frac{\tilde{\rho}_0 \mu}{\sqrt{1 + \mu^2}} \right) \\ &\quad \cdot e^{(-\mu + \sqrt{1 + \mu^2})\tau_d} (-\mu + \sqrt{1 + \mu^2}) \\ \theta_d &= \frac{3\pi}{2} + \Omega \tau_d, \end{aligned} \quad (5)$$

where v_x is the horizontal velocity, v_y is the vertical velocity, Ω is the sprocket rotational speed, μ is the coefficient of friction, $\tilde{\rho}_0$ is coefficient of radial distance, and τ_d is the travel time of grain and can be obtained from

$$\begin{aligned} 1 &= \frac{1}{2} \left(\tilde{\rho}_0 - \frac{\tilde{\rho}_0 \mu}{\sqrt{1 + \mu^2}} \right) e^{(-\mu - \sqrt{1 + \mu^2})\tau_d} \\ &\quad + \frac{1}{2} \left(\tilde{\rho}_0 + \frac{\tilde{\rho}_0 \mu}{\sqrt{1 + \mu^2}} \right) e^{(-\mu + \sqrt{1 + \mu^2})\tau_d}. \end{aligned} \quad (6)$$

2.1.4. Flight Stage. The impact force caused by grain can be expressed as

$$F = \begin{cases} \frac{V}{d} \int_{\rho_{\text{crit}}}^1 (\nu_x \sin \phi - \nu_y \cos \phi) \sin \phi (1 + e) \rho h^{-1}(\rho) \eta w d\rho & \rho_{\text{crit}} > h_0 \\ \frac{V}{d} \int_{h_0}^1 (\nu_x \sin \phi - \nu_y \cos \phi) \sin \phi (1 + e) \rho h^{-1}(\rho) \eta w d\rho & h_0 > \rho_{\text{crit}}, \end{cases} \quad (7)$$

where F is impact force, ϕ is installation angle of grain flow sensor, e is the coefficient of restitution, $h^{-1}(\rho)$ is used to compute the opening angle ψ , and $h(\psi) = \rho \rho_{\text{crit}}$ is the critical radius, which meet the condition: $\lambda > 0$, $\kappa = 0$. λ and κ are calculated as follows:

$$\lambda = \frac{(d_x - l \cos \theta_d) \sin \phi - (d_y - l \sin \theta_d) \cos \phi}{\nu_x \sin \phi - \nu_y \sin \phi}, \quad (8)$$

$$\kappa = \frac{\nu_x (d_y - l \sin \theta_d) - \nu_y (d_x - l \cos \theta_d)}{\nu_y \cos \phi - \nu_x \sin \phi},$$

where d_x is the horizontal distance between the lowest point of grain flow sensor and sprocket center and d_y is the vertical distance between the lowest point of grain flow sensor and sprocket center.

DGFM is represented by (7), which describes a physical relationship between the impact force and the grain flow with multiple parameters. The simplified form of the model is as follows:

$$F = f(\dot{m}, \mu, e, \eta, h_f, V, d, \Omega, l, w, d_x, d_y, \phi). \quad (9)$$

In (9), as discussed above, the eight parameters $[V \ d \ \Omega \ l \ w \ d_x \ d_y \ \phi]$ are the machine geometric parameters obtained by measurement; the four parameters $[\mu \ e \ \eta \ h_f]$ are theoretical parameters to be estimated, and $f(*)$ is the value calculated with DGFM. Mass flow is calculated by applying a bisection algorithm to DGFM. Establishment and application of the DGFM can be found in the literature [23].

2.2. Objective Function. As discussed above, the DGFM consists of four unknown parameters. Unknown parameter estimation problem can be transformed into an optimization problem by minimizing a root mean square error (RMSE). For this purpose, the impact force is measured and computed by grain flow sensor and DGFM, respectively. Unknown parameters are estimated by the proposed objective function defined as follows:

$$\text{RMSE} = \sqrt{\frac{1}{M} \sum_{i=1}^M (F_i - F'_i)^2}, \quad (10)$$

where M is the number of samples, F_i is the i th calculated impact force in terms of (9), and F'_i is the i th measured impact force.

2.3. Review of ABC Algorithm. The ABC algorithm simulating the foraging process of honey bees was proposed to solve complex optimization problems [24]. ABC algorithm

contains three types of bees: employed bees, onlooker bees, and scout bees. Three types of bees share the information of the food sources with each other. Employed bees find the food sources and deliver the information of the food sources to onlooker bees in the hive. Onlooker bees follow employed bees to explore the food sources based on the information they have received. In the process of looking for the food sources, if the food source is not improved after a continuous trial at predetermined value, then employed bee abandon that food sources and turn into a scout searching around randomly. Predetermined value for abandoning a food source is called "limit," which is an important control parameter in the ABC algorithm. The flow of the ABC algorithm is listed as follows.

Step 1. N food sources are generated randomly from the following:

$$x_{ij} = x_j^{\min} + \text{rand}[0, 1] (x_j^{\max} - x_j^{\min}), \quad (11)$$

where x_{ij} represents that artificial bee is at the j th position of the i th food source; $i = 1, 2, \dots, N$; $j = \text{rand}[1, 2, \dots, n]$; N is the number of food sources; n is the search space dimension; $x_j^{\min}$ and $x_j^{\max}$ are the upper and lower limits of the j th variable, respectively.

Step 2. If the current food position is $X_i = [x_{i1}, x_{i2}, \dots, x_{in}]$, the following solution search equation is used by the employed bees to generate a new food source $V_i = [x_{i1}, x_{i2}, \dots, v_{ij}, \dots, x_{in}]$.

$$v_{ij} = x_{ij} + \theta_{ij} (x_{ij} - x_{kj}), \quad (12)$$

where v_{ij} represents the position of new source found by the i th employed bee, $i = 1, 2, \dots, N$, $j = \text{rand}[1, 2, \dots, n]$, $k \in \{1, 2, \dots, N\}$, and $k \neq i$; θ_{ij} is a random number selected from $[-1, 1]$.

Step 3. Each onlooker bee chooses and follows the employed bees based on the quality of food sources. The quality of food sources denoted as P_i is given by

$$P_i = \frac{\text{fit}_i}{\sum_{i=1}^N \text{fit}_i}, \quad (13)$$

where fit_i is the fitness value of the i th solution. For a minimization problem, the fitness value of a solution can be defined as

$$\text{fit}_i = \begin{cases} \frac{1}{1 + f(X_i)} & \text{if } f(X_i) > 0 \\ 1 + |f(X_i)| & \text{if } f(X_i) \leq 0, \end{cases} \quad (14)$$

where $f(X_i)$ is the value of the objective function at X_i .

Step 4. If a food source fails to get better after predetermined value “limit,” then that food source needs to be abandoned. The employed bees become scouts later. A new food source is randomly generated in space using (11).

3. IABC Algorithm

This section presents the detailed description of the proposed improved artificial bee colony (IABC) algorithm. There are two improvements on basic ABC algorithm: modifying the search method of the onlooker bees and proposing a novel probability model.

3.1. Search Method for the Onlooker Bees. In ABC, production of new food source (see in (12)) reduces the effectiveness of algorithm because existing information is not used to produce new food source. Inspired by differential evolution (DE), Zhu and Kwong [25], proposed a modified ABC algorithm (MABC) which uses information of global best food source. Search method of MABC can be expressed as follows:

$$v_{ij} = x_{\text{best},j} + \theta_{ij} (x_{r_1,j} - x_{r_2,j}), \quad (15)$$

where X_{best} is the best food source in the all food source. The indices r_1 and r_2 are mutually exclusive integers randomly chosen from $\{1, 2, \dots, N\}$ and different from the base index i .

In IABC, the search method of MABC is modified to further improve the exploitation. The new method used to calculate a new food source is shown in

$$v_{ij} = x_{\text{best},j} + \theta_{ij} (x_{\text{best},j} - x_{r_2,j}). \quad (16)$$

Compared with (15), (16) not only produces the new food source around the best food source but also makes use of the information of the best food source to guide the search trajectory. Thus, the exploitation of algorithm is improved greatly.

3.2. Probability Model. It is obvious that (16) has a good capability of exploitation. As a result, the diversity of population decreases. In IABC, hence, a probability model is used to increase the diversity of population, and it can be expressed as follows:

$$P_i = 0.8 \times \frac{\text{fit}_i}{\text{fit}_{\max}} + 0.2, \quad (17)$$

where $\text{fit}_{\max}$ is the maximum fitness value of population.

In (17), values 0.8 and 0.2 are the optimal through simulation test and ensure some diversity in the case when one solution is superior to all others by allowing 20% of onlooker bees to select different solution.

From the above analysis, two equations are modified ((12) and (13) are replaced with (16) and (17), resp.), but the main framework of IABC is consistent with that of ABC.

4. Simulation Results and Analysis

A set of six benchmark functions is applied to verify the performance of IABC in the simulation experiments. The benchmark functions are summarized in Table 1.

TABLE 1: Detail for the 6 benchmark functions used in experiments.

Functions	Dimension	Search range	Optimum value
Rosenbrock	2 and 3	$[-30, 30]$	0
Schaffer	2 and 3	$[-100, 100]$	0
Rastrigin	30 and 60	$[-5.12, 5.12]$	0
Griewank	30 and 60	$[-600, 600]$	0
Sphere	30 and 60	$[-100, 100]$	0
Ackley	30 and 60	$[-32, 32]$	0

Three ABC variants, GABC [25], MABC [26], and EABC [27], are used to compare with IABC. To be fair, the population size is set to 80 that are the same as that in [25]. To investigate the effect of *limit*, a test is made on four 30-dimensional test functions (Sphere, Griewank, Rastrigin, and Ackley) with IABC and the results are shown in Table 2. As seen from Table 2, *limit* can influence the optimization results. For the Griewank function, a faster convergence speed and better results are obtained, when *limit* is 200. For the other three test functions, the effect of *limit* on the performance of IABC is very little except Rastrigin at *limit* = 400. Therefore, in our experiments, the limit is set to 200 for all test functions.

Given the above, the population size, the maximum number of generations, and the *limit* values are set to 80, 5000, and 200, respectively. To be specific, the constant value C is equal to 1.5 in GABC and the selective probability P is set to 0.7 in MABC. Each of the experiments is repeated 30 times independently. The final results are given in Table 3.

Table 3 clearly shows that IABC works better than ABC, GABC, EABC, and MABC. Although the result of IABC is inferior to that of MABC on the Rosenbrock, there is little difference between MABC and IABC. And it is worth noting that IABC maintains the framework of original ABC and does not use chaotic maps and opposition-based learning techniques that are used in the initialization step of MABC.

Figure 2 presents the convergence curves of ABC, GABC, MABC, and IABC on six benchmark functions with different dimension. From Figure 2, accuracy and convergence rate of IABC has been greatly improved compared to ABC, GABC, and MABC algorithm.

5. Parameter Estimation of Dynamic Grain Flow Model with IABC

To make it more accurate for DGFM to calculate grain flow, it is very necessary to use a more efficient optimization algorithm to solve parameters estimation problem of DGFM. In view of the excellent performance of the proposed IABC algorithm in this paper, the IABC algorithm is used for parameters estimation of DGFM. A schematic diagram of the approach is illustrated in Figure 3.

Impact force and grain flow signals were obtained from a test rig illustrated in Figure 4. The experiment conditions are as follows: a novel grain flow sensor was installed at the top of the clean grain elevator, using PVDF piezoelectric film as the active element to measure the impact force [28, 29]. Grain flow was measured by weighing sensor with accuracy of

FIGURE 2: Convergence performance of ABC, GABC, MABC, and IABC on six benchmark functions.

TABLE 2: Effect of *limit* on the performance of IABC.

Maximum number of generations	Dimension	Limit		Functions			
				Rastrigin	Griewank	Sphere	Ackley
1000	30	100	Mean	0	$7.24e-11$	$5.58e-27$	$1.42e-11$
			Std	0	$2.65e-11$	$7.41e-27$	$5.75e-12$
1000	30	200	Mean	0	$2.96e-12$	$1.32e-27$	$1.26e-13$
			Std	0	$4.99e-12$	$2.65e-28$	$3.48e-14$
1000	30	300	Mean	0	$2.36e-11$	$2.95e-27$	$1.28e-13$
			Std	0	$4.99e-11$	$3.19e-27$	$2.66e-14$
1000	30	400	Mean	$4.64e-5$	$2.33e-10$	$1.72e-26$	$1.33e-13$
			Std	$1.93e-5$	$3.15e-10$	$2.84e-26$	$3.69e-14$

FIGURE 3: Schematic diagram of parameter estimation of DGFM.

0.05%. The sprocket rotational speed was measured by speed sensor. Frequency converter was used to change the motor speed and the sprocket rotational speed. Signal modulate circuit was necessary to bring signals to an acceptable range for recording. The data acquisition system consisted of NI USB-6216 card and computer and LABVIEW software, and the sample rate was set at 150 Hz. All experimental data were preprocessed using EMD [30]. The theoretical parameters were estimated based on the machine geometric parameters and experimental data from test rig in the sprocket rotational speed of 320 r/min, 360 r/min, and 400 r/min, respectively. The machine geometric parameters are summarized in Table 4.

To estimate the theoretical parameters of DGFM, the population size, the maximum number of generations, and the *limit* values are set to 80, 1000, and 100, respectively. Figure 5 shows the $F-\dot{m}$ curve of DGFM and experimental data points, respectively. As seen from Figure 5, the $F-\dot{m}$ curves got by IABC are perfectly matched with the real data points. The accuracy of the proposed method is confirmed by this observation.

To verify the superiority of IABC algorithm in parameter estimation of DGFM, the IABC algorithm is compared with nonlinear least squares (NLS), particle swarm optimization (PSO), and genetic algorithm (GA). In all experiments in this section, the population size and the maximum number of generations used in each algorithm were chosen to be the same as the IABC algorithm, respectively. The other specific parameters of algorithms are given below.

For PSO algorithm, the learning rates c_1 and c_2 are both 2.05; the constriction factor $\chi = 0.729$. For GA algorithm, a

binary coded standard GA with elite units, random selection, and crossover mutation was used in the experiment. Meanwhile, single point crossover operation with the rate of 0.8 and stochastic uniform sampling technique were employed in the experiment. Mutational manipulation resumes the loss of genetic diversity during replication and hybridization applications. Mutation rate was set to be 0.01.

Table 5 illustrates the estimated results for the theoretical parameters of DGFM when four algorithms are applied. For comparing purposes, the values of RMSE are also listed in Table 5. As it can be observed, the theoretical parameters are relatively insensitive to changes of the sprocket rotational speed. IABC and PSO result in relatively closer values of RMSE compared to NLS and GA under different sprocket rotational speed.

To make a better comparison between IABC and PSO, search range of the theoretical parameters was enlarged. The comparison results are shown in Table 6. The value of RMSE increases obviously due to enlarging search range from Table 6; however, under different sprocket rotational speed the values of RMSE obtained by IABC algorithm are $7.62e-3$, $6.99e-3$, and $7.15e-3$, respectively, which are still better than the results obtained by PSO ($2.36e-2$, $1.58e-2$, and $2.69e-2$). Figure 6 shows that the convergence rate of IABC algorithm is better than PSO algorithm at sprocket rotational speed of 360 r/min. The above results show that IABC has stronger search ability for complex optimization problems and can obtain higher accuracy solutions. Therefore, IABC algorithm is better than NLS algorithm, GA algorithm, and PSO algorithm in estimating parameters of DGFM.

6. Conclusions

This paper presented a method of estimating parameters of DGFM using IABC algorithm. In the proposed algorithm, the research method of original ABC was modified to improve its convergence rate. But the research method resulted in diversity loss, so a probability model was proposed to maintain diversity of population. With testing against a set of six benchmark functions, the IABC algorithm had a better performance than the other ABC variants. Then, the proposed algorithm was used to estimate parameters of DGFM. By comparing IABC algorithm with NLS algorithm,

TABLE 3: The final results comparison of IABC, MABC, GABC, EABC, and ABC.

Functions	Dimension	ABC			GABC			MABC			EABC			IABC		
		Mean	Std	Mean	Mean	Std	Mean	Mean	Std	Mean	Mean	Std	Mean	Mean	Std	Std
Rosenbrock	2	4.20e-03	4.20e-03	1.68e-04	1.45e-04	1.45e-04	4.99e-06	8.22e-06	8.22e-06	4.63e-04	4.57e-04	4.57e-04	9.75e-06	2.07e-05		
	3	3.75e-03	7.55e-02	2.66e-03	2.22e-03	2.22e-03	5.52e-06	3.03e-06	3.03e-06	1.20e-02	7.06e-03	7.06e-03	5.89e-05	1.13e-04		
Schaffer	2	0	0	0	0	0	0	0	0	0	0	0	0	0		
	3	1.96e-07	6.07e-07	1.11e-17	2.34e-17	2.34e-17	0	0	0	2.79e-07	2.24e-07	2.24e-07	0	0		
Rastrigin	30	1.52e-14	2.56e-14	1.32e-14	2.44e-14	2.44e-14	0	0	0	9.97e-15	3.87e-15	3.87e-15	0	0		
	60	8.60e-13	1.97e-12	2.99e-13	1.78e-13	1.78e-13	0	0	0	7.51e-13	6.15e-13	6.15e-13	0	0		
Griewank	30	2.41e-16	2.97e-16	2.96e-17	4.99e-17	4.99e-17	0	0	0	4.90e-15	7.31e-15	7.31e-15	0	0		
	60	3.89e-13	2.10e-12	1.43e-15	1.38e-16	1.38e-16	0	0	0	4.19e-14	9.05e-13	9.05e-13	0	0		
Sphere	30	6.38e-16	1.20e-15	2.96e-17	4.99e-17	4.99e-17	2.95e-31	1.19e-30	1.19e-30	1.67e-16	2.70e-16	2.70e-16	4.60e-150	7.99e-150		
	60	2.28e-15	3.18e-16	7.55e-16	4.13e-16	4.13e-16	6.93e-21	1.25e-20	1.25e-20	1.41e-15	1.82e-15	1.82e-15	3.72e-70	6.88e-70		
Ackley	30	4.14e-14	4.02e-15	3.33e-14	3.19e-15	3.19e-15	1.72e-14	2.84e-15	2.84e-15	1.22e-14	4.86e-15	4.86e-15	1.23e-14	2.15e-15		
	60	1.03e-13	8.96e-15	8.83e-14	6.23e-15	6.23e-15	6.62e-14	1.74e-15	1.74e-15	1.55e-13	2.84e-15	2.84e-15	5.23e-14	1.54e-15		

TABLE 4: Machine geometric parameters of test rig.

V (m/s)	D (m)	l (m)	w (m)	d (m)	d_x (m)	d_y (m)	Φ (°)
$\Omega \times w$	0.176	0.151	0.074	0.367	0.326	0.021	70

TABLE 5: Comparison of estimated performance for NLS, PSO, GA, and IABC.

Sprocket rotational speed (r/min)	Parameters	Search range	Algorithm			
			NLS	PSO	GA	IABC
320	μ	0~1	0.186	0.213	0.192	0.216
	e	0~1	0.054	0.069	0.059	0.068
	η	750~2000	1081.9	1123.6	1098.3	1123.3
	h_f	0~5	1.984	2.112	2.031	2.118
	RMSE		0.013	$9.91e-4$	$8.63e-3$	$9.76e-4$
	Std		0.032	$8.45e-4$	$6.25e-3$	$7.66e-4$
360	μ	0~1	0.181	0.214	0.195	0.219
	e	0~1	0.056	0.066	0.058	0.067
	η	750~2000	1081.1	1123.8	1099.9	1123.5
	h_f	0~5	1.989	2.114	2.036	2.119
	RMSE		0.012	$9.36e-4$	$8.96e-3$	$9.23e-4$
	Std		0.009	$9.12e-4$	$1.38e-2$	$8.47e-4$
400	μ	0~1	0.187	0.216	0.193	0.212
	e	0~1	0.057	0.067	0.053	0.065
	η	750~2000	1081.6	1123.1	1099.5	1123.4
	h_f	0~5	1.981	2.111	2.038	2.117
	RMSE		0.014	$9.41e-4$	$8.72e-3$	$9.42e-4$
	Std		0.065	$9.89e-4$	$9.65e-3$	$8.12e-4$

TABLE 6: Comparison of estimated performance for IABC and PSO.

Algorithm	Parameters	Search range	Sprocket rotational speed (r/min)		
			320	360	400
IABC	μ	-1~2	0.198	0.197	0.193
	e	-1~2	0.061	0.069	0.065
	η	100~3000	1118.6	1118.6	1119.3
	h_f	-5~10	1.921	1.929	1.932
	RMSE		$6.62e-3$	$5.61e-3$	$7.15e-3$
	Std		$4.56e-3$	$4.26e-3$	$6.42e-3$
PSO	μ	-1~2	0.179	0.181	0.186
	e	-1~2	0.056	0.056	0.058
	η	100~3000	1095.6	1092.8	1094.7
	h_f	-5~10	1.881	1.893	1.863
	RMSE		$3.36e-2$	$3.48e-2$	$3.69e-2$
	Std		$5.63e-2$	$3.12e-2$	$2.53e-2$

FIGURE 4: Schematic of test rig for DGFM.

FIGURE 5: $F-\dot{m}$ curve of DGFM (using IABC algorithm) and the experimental data points.

FIGURE 6: Comparison of convergence curves of IABC and PSO at sprocket rotational speed of 360 r/min.

GA algorithm, and PSO algorithm, the proposed algorithm had higher accuracy solutions and a faster convergence rate, which is more suitable for parameter estimation of DGFM.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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