Journal of King Saud University – Engineering Sciences 36 (2024) 330–338

Contents lists available at ScienceDirect

Journal of King Saud University – Engineering Sciences

journal homepage: www.sciencedirect.com

Original article

Augmented hunger games search algorithm using logarithmic spiral opposition-based learning for function optimization and controller design

Davut Izci [a], Serdar Ekinci [b,*], Erdal Eker [c], Murat Kayri [d]

[a] Department of Electronics & Automation, Batman University, Batman 72060 Turkey
[b] Department of Computer Engineering, Batman University, Batman 72100, Turkey
[c] Vocational School of Social Sciences, Mus Alparslan University, Mus, Turkey
[d] Department of Computer and Instructional Technology Education, Van Yuzuncu Yil University, Van, Turkey

ARTICLE INFO

Article history:
Received 19 August 2021
Accepted 5 March 2022
Available online 11 March 2022

Keywords:
Magnetic ball suspension system
FOPID controller
Hunger games search algorithm
Logarithmic spiral
Opposition-based learning technique

ABSTRACT

This paper explains the construction of a novel augmented hunger games search algorithm using a logarithmic spiral opposition-based learning technique. The proposed algorithm (LsOBL-HGS) is used as an efficient tool for both function optimization and controller design. To assess the performance of the algorithm for function optimization, benchmark functions from the CEC2017 test suite were employed and comparisons were made with available and good performing algorithms. In terms of controller design, the proposed LsOBL-HGS algorithm was utilized to design a FOPID controlled magnetic ball suspension system. Comparative assessments were also performed for FOPID controller design, as well using other state-of-the-art methods reported for the magnetic ball suspension system. The results showed that the proposed LsOBL-HGS algorithm has good capability for FOPID controller design employed in a magnetic ball suspension system as it provided an improvement of more than 13% in terms of the transient response-related parameters and more than 34% in terms of bandwidth compared to the best-reported approach used for comparisons.
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1. Introduction

Magnetic suspension refers to magnetic-based non-contact lifting which has promising potential for real-world engineering applications, therefore it keeps gaining significant attention amongst researchers. The employment of magnetic-based non-contact lifting can be observed in high-speed trains, vibration isolation, and non-friction bearings. However, an appropriate controller mechanism must be integrated with the magnetic suspension systems as this concept has a nonlinear and unstable structure. Therefore, different controlling mechanisms have so far been reported for this purpose (Acharya et al., 2020; Ahmad et al., 2014; Bauer and Baranowski, 2020; García-Gutiérrez et al., 2019; Mughees and Mohsin, 2020; Sadek et al., 2017). The wider employment of proportional-integral-derivative (PID) controllers can easily be observed amongst the available mechanisms which is due to their relatively easier applicability (Yadav et al., 2016). However, for an increased capability, fractional-order PID (FOPID) controllers are more demanding (Izci and Ekinci, 2021). Because the latter one utilizes fractional terms, it can provide an additional degree of freedom which makes them desirable candidates for dynamic systems (Altbawi et al., 2021; George et al., 2022; Izci et al., 2022b; Kommula and Kota, 2020).

Appropriate tuning schemes for parameter adjustments are required to benefit from the advantages of the aforementioned controllers. In that sense, the metaheuristic algorithms can be employed as unbeatable candidates to tune controllers employed in magnetic ball suspension systems (Roy et al., 2016). Some of the related examples are manta ray foraging optimization (Ekinci et al., 2021), slime mould algorithm (Izci et al., 2021), grey wolf optimization (Ataşlar-Ayyıldız et al., 2021), and particle swarm optimization (Ataşlar-Ayyıldız et al., 2021; Zhang et al., 2021) along with bird swarm algorithm and elephant herding optimiza-

* Corresponding author.
E-mail addresses: davut.izci@batman.edu.tr (D. Izci), serdar.ekinci@batman.edu.tr (S. Ekinci), e.eker@alparslan.edu.tr (E. Eker), muratkayri@yyu.edu.tr (M. Kayri).
Peer review under responsibility of King Saud University.

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https://doi.org/10.1016/j.jksues.2022.03.001
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tion (Dey et al., 2021). Considering the demonstrated promise of those metaheuristic techniques, this paper aims to use an augmented hunger games search (HGS) algorithm (Yang et al., 2021) to tune a FOPID controller for a magnetic ball suspension system to reach better performance compared to previously reported works.

In this study, an opposition-based learning (OBL) technique (Tizhoosh, 2005) was used to enhance the HGS algorithm. The latter technique increases the probability of finding a solution closer to the global optimum. Different examples of OBL versions and their role for performance improvement of the metaheuristic algorithms can be seen in the literature. Some of the recent examples can be listed as shuffled frog-leaping algorithm (Sharma and Pant, 2018), grey wolf optimizer (Long et al., 2019), Harris hawks optimization (Gupta et al., 2020), tunicate swarm algorithm (Sharma et al., 2021) and Lévy flight distribution algorithm (Izci et al., 2022a). Unlike the listed studies, this paper proposes a logarithmic spiral (Mirjalili and Lewis, 2016) version of the OBL technique to enhance the HGS algorithm so that the probability of finding the global optimum increases significantly.

To justify the capability of the augmented HGS using logarithmic spiral opposition-based learning (LsOBL-HGS) algorithm for function optimization, a CEC2017 test suite was employed as it includes challenging benchmark functions for evaluation of the algorithms. The comparative assessment of the proposed LsOBL-HGS algorithm was performed against grey wolf optimization (Mirjalili et al., 2014), Harris hawks optimization (Heidari et al., 2019), and aquila optimization (Abualigah et al., 2021) algorithms as well as the original version of HGS (Yang et al., 2021) algorithm. Then, a FOPID controller was designed based on the proposed LsOBL-HGS algorithm for a magnetic ball suspension system in order to assess the ability of the proposed algorithm for a real-world complex engineering optimization problem. A performance index called *ZLG* (Izci et al., 2022c) was adopted as an objective function to reach the optimal parameters of the FOPID controller. Several comparative assessments were carried out for the latter task using other reported state-of-the-art methods of artificial electric field algorithm based FOPID controller (Demirören et al., 2021), artificial bee colony algorithm based FOPID controller (Demirören et al., 2021), and atom search optimization based FOPID controller (Demirören et al., 2021). All the analyses related to function optimization and the controller design for the magnetic ball suspension system showed superior capability of the proposed LsOBL-HGS algorithm for different optimization problems.

2. Hunger games search algorithm

The animals' instinct to survive has motivated the development of the HGS algorithm (Yang et al., 2021). The hunger-driven activities and behavioral choices amongst the animals are considered as a set of game rules by the HGS algorithm. During foraging, social animals mainly cooperate; however, few individuals may not take part. Such a cooperative communication and foraging behavior is represented by Eq. (1):

$$\overrightarrow{X(t+1)} = \begin{cases} Game_1 : \overrightarrow{X(t)} \cdot (1 + randn(1)), r_1 < l \\ Game_2 : \overrightarrow{W_1} \cdot \overrightarrow{X_b} + \vec{R} \cdot \overrightarrow{W_2} \cdot \left| \overrightarrow{X_b} - \overrightarrow{X(t)} \right|, r_1 > l, r_2 > E \\ Game_3 : \overrightarrow{W_1} \cdot \overrightarrow{X_b} - \vec{R} \cdot \overrightarrow{W_2} \cdot \left| \overrightarrow{X_b} - \overrightarrow{X(t)} \right|, r_1 > l, r_2 < E \end{cases} \quad (1)$$

where two random numbers, within the range of $[0, 1]$, are denoted by r_1 and r_2; the current iteration is shown by t , and a random number satisfying normal distribution is represented by $randn(1)$. The hunger weights are denoted by W_1 and W_2. The locations of each agent and the best agent are represented by $X(t)$ and X_b, respectively, for the current iteration. The parameter of l helps improve the algorithm. R represents a number, within $[-\alpha, \alpha]$, which is calculated as follows:

$$\vec{R} = 2 \times shrink \times rand - shrink \quad (2)$$

where $shrink = 2 \times (1 - \frac{t}{T})$, $rand$ is a random number within $[0, 1]$ and T is the maximum number of iterations. The parameter of E, given in Eq. (1), stands for a variation control for all positions and is defined as:

$$E = sech(|F(i) - BF|), i \in 1, 2, \cdots, n \quad (3)$$

where $F(i)$ and BF are the fitness value of each agent and the best fitness value, respectively, obtained so far. The hyperbolic function of *sech* is defined as $2/(e^x + e^{-x})$. The starvation characteristics of the individuals are mathematically simulated by the hunger weights which are defined in Eqs. (4) and (5):

$$\overrightarrow{W_1(i)} = \begin{cases} hng(i) \cdot \frac{N}{Shng} \times r_4, r_3 < l \\ 1, r_3 > l \end{cases} \quad (4)$$

$$\overrightarrow{W_2(i)} = (1 - e^{-|hng(i) - Shng|}) \times r_5 \times 2 \quad (5)$$

where N denotes the number of individuals and hng is the hunger for individuals. Besides, r_3, r_4 and r_5 are all random numbers within the range of $[0, 1]$, and $Shng$ denotes the sum of hungry feelings of all individuals. The parameter of $hng(i)$ is defined as follows:

$$hng(i) = \begin{cases} 0, Allfit(i) == BF \\ hng(i) + H, Allfit(i)! = BF \end{cases} \quad (6)$$

where $Allfit(i)$ holds the fitness of each agent in the current iteration and BF stands for the best fitness obtained so far.

The term of H denotes hunger sensation which is calculated as follows:

$$H = \begin{cases} LH \times (1 + r), TH < LH \\ TH, TH \geq LH \end{cases} \quad (7)$$

where $TH = (F(i) - BF/(WF - BF)) \times r_6 \times 2 \times (UB - LB)$. In the above equation, LH stands for the lower bound whereas UB and LB are the feature space-related upper and lower bounds, respectively. $F(i)$ represents the fitness value of each agent and WF denotes the worst fitness value obtained so far. Fig. 1 represents the logic of the HGS algorithm for the optimization tasks.

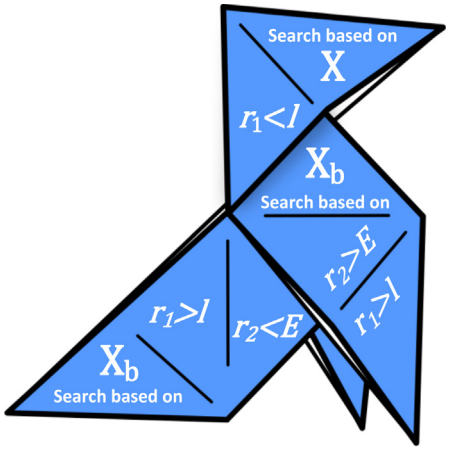


Fig. 1. The logic of the HGS algorithm (Yang et al., 2021).

Table 1
Statistical results of CEC2017 benchmark functions.

Function ID	Index	LsOBL-HGS	HGS	GWO	HHO	AO
F1	Mean	6.3653E + 03	7.0169E + 03	4.0610E + 06	3.2043E + 05	5.2861E + 05
	Std	4.3602E + 03	4.5034E + 03	1.1985E + 07	1.7349E + 05	3.7558E + 05
F3	Mean	3.0000E + 02	3.0407E + 02	1.3305E + 03	3.0194E + 02	4.3646E + 02
	Std	3.7683E − 04	4.1351E − 01	1.4570E + 03	8.2897E − 01	1.2893E + 02
F4	Mean	4.0215E + 02	4.1629E + 02	4.1654E + 02	4.1373E + 02	4.0906E + 02
	Std	1.6369E + 00	1.7549E + 01	1.1913E + 01	2.6009E + 01	2.6773E + 00
F5	Mean	5.1301E + 02	5.3111E + 02	5.1662E + 02	5.4745E + 02	5.3048E + 02
	Std	6.2533E + 00	8.2482E + 00	7.9230E + 00	1.6628E + 01	1.0244E + 01
F6	Mean	6.0047E + 02	6.0086E + 02	6.0112E + 02	6.3386E + 02	6.1767E + 02
	Std	4.9390E − 01	5.8827E − 01	1.1589E + 00	9.4315E + 00	7.4753E + 00
F7	Mean	7.2426E + 02	7.3922E + 02	7.3146E + 02	7.7836E + 02	7.4321E + 02
	Std	1.0510E + 01	1.0563E + 01	1.5206E + 01	1.6991E + 01	1.2803E + 01
F8	Mean	8.0797E + 02	8.1952E + 02	8.1523E + 02	8.3397E + 02	8.2138E + 02
	Std	4.4509E + 00	6.7994E + 00	5.4020E + 00	7.3463E + 00	8.1810E + 00
F9	Mean	9.0003E + 02	9.0076E + 02	9.0889E + 02	1.3815E + 03	9.8064E + 02
	Std	1.2256E − 01	2.6252E + 00	1.6225E + 01	2.3865E + 02	1.1529E + 02
F10	Mean	1.4293E + 03	1.6081E + 03	1.5204E + 03	2.0521E + 03	1.7943E + 03
	Std	2.0268E + 02	2.8205E + 02	2.2130E + 02	3.7043E + 02	2.4160E + 02
F11	Mean	1.1260E + 03	1.1426E + 03	1.1461E + 03	1.1706E + 03	1.1837E + 03
	Std	2.0199E + 01	4.5226E + 01	6.4788E + 01	4.8788E + 01	4.8085E + 01
F12	Mean	8.3420E + 03	2.0088E + 04	7.6224E + 05	2.9705E + 06	3.7110E + 06
	Std	3.8655E + 03	2.0504E + 04	7.8042E + 05	2.9031E + 06	3.8531E + 06
F13	Mean	5.7306E + 03	1.1601E + 04	1.2213E + 04	1.8435E + 04	1.8428E + 04
	Std	5.0020E + 03	6.7794E + 03	9.5275E + 03	1.2193E + 04	1.4134E + 04
F14	Mean	1.4674E + 03	2.5539E + 03	2.9096E + 03	1.6381E + 03	1.8429E + 03
	Std	5.4467E + 01	1.6348E + 03	1.8624E + 03	1.4231E + 02	2.9225E + 02
F15	Mean	3.1890E + 03	4.2862E + 03	4.9329E + 03	4.9655E + 03	4.4719E + 03
	Std	2.9484E + 03	2.7760E + 03	1.7729E + 03	1.3857E + 03	1.6239E + 03
F16	Mean	1.7352E + 03	1.7595E + 03	1.7807E + 03	1.8054E + 03	1.7678E + 03
	Std	1.0251E + 02	1.3625E + 02	1.2253E + 02	1.4939E + 02	1.2409E + 02
F17	Mean	1.7181E + 03	1.7605E + 03	1.8206E + 03	1.7663E + 03	1.7758E + 03
	Std	2.1152E + 01	4.6985E + 01	4.3391E + 01	3.3727E + 01	2.2756E + 01
F18	Mean	2.0802E + 04	2.3978E + 04	3.1449E + 04	1.6759E + 04	2.5521E + 04
	Std	1.1300E + 04	1.4398E + 04	1.5085E + 04	1.2793E + 04	1.4708E + 04
F19	Mean	3.3399E + 03	1.1699E + 04	6.3225E + 03	9.7714E + 03	6.3080E + 03
	Std	1.9350E + 03	1.1134E + 04	5.8568E + 03	8.1075E + 03	5.7503E + 03
F20	Mean	2.0127E + 03	2.0216E + 03	2.1210E + 03	2.1687E + 03	2.1175E + 03
	Std	9.3435E + 00	1.1342E + 01	4.7479E + 01	7.7306E + 01	5.6107E + 01
F21	Mean	2.2190E + 03	2.3710E + 03	2.3170E + 03	2.3097E + 03	2.2906E + 03
	Std	3.2251E + 01	3.3974E + 01	6.6931E + 00	5.9256E + 01	5.7181E + 01
F22	Mean	2.2626E + 03	2.3131E + 03	2.3486E + 03	2.4552E + 03	2.3008E + 03
	Std	1.7262E + 01	1.0733E + 02	3.0446E + 01	2.4480E + 02	8.9167E + 00
F23	Mean	2.6158E + 03	2.6239E + 03	2.6228E + 03	2.6869E + 03	2.6470E + 03
	Std	5.6411E + 00	6.4239E + 00	8.3269E + 00	2.4361E + 01	1.4580E + 01
F24	Mean	2.6042E + 03	2.7792E + 03	2.7439E + 03	2.7155E + 03	2.7356E + 03
	Std	8.9321E + 01	1.2627E + 01	1.4595E + 01	1.1826E + 02	7.1265E + 01
F25	Mean	2.9194E + 03	2.9329E + 03	2.9484E + 03	2.9408E + 03	2.9161E + 03
	Std	3.1642E + 01	3.3730E + 01	2.3786E + 01	2.1743E + 01	2.1498E + 01
F26	Mean	2.9645E + 03	3.2376E + 03	2.9886E + 03	3.3700E + 03	2.9356E + 03
	Std	2.1066E + 02	4.3722E + 02	3.1668E + 02	4.6435E + 02	1.5733E + 02
F27	Mean	3.0878E + 03	3.0958E + 03	3.1274E + 03	3.1807E + 03	3.1038E + 03
	Std	2.2515E + 00	1.7410E + 01	1.8878E + 01	5.1694E + 01	4.1658E + 00
F28	Mean	3.2208E + 03	3.2559E + 03	3.3622E + 03	3.3503E + 03	3.3917E + 03
	Std	1.2620E + 02	1.4485E + 02	1.0235E + 02	1.5171E + 02	1.0682E + 02
F29	Mean	3.1747E + 03	3.2371E + 03	3.2124E + 03	3.3541E + 03	3.2417E + 03
	Std	3.2944E + 01	5.6416E + 01	7.4610E + 01	1.2806E + 02	5.7123E + 01
F30	Mean	1.9927E + 05	3.5948E + 05	5.6525E + 05	1.3405E + 06	4.1545E + 05
	Std	3.6602E + 05	5.4532E + 05	6.7458E + 05	1.5193E + 06	5.3863E + 05

3. Proposed novel LsOBL-HGS algorithm

The OBL strategy is capable of enhancing the exploration of the algorithms since it provides the opportunity of avoiding local stagnation (Izci et al., 2020). The OBL mechanism can be explained as $X_{op} = UB + LB - X$ where X is a real number within boundaries of $[LB, UB]$ and X_{op} is the opposite of that number. In the OBL, X and X_{op} are considered together and the best N solutions are selected from their union.

In this study, an augmented HGS algorithm is proposed using a logarithmic spiral OBL (LsOBL) technique. The HGS algorithm firstly finds the optimal position so far (X_{best}). Then the opposite position of X_{op} is obtained with the modified OBL technique using the following form:

$$X_{op} = \varphi_1 \cdot UB + \varphi_2 \cdot LB - X_{best} \tag{8}$$

where φ_1 and φ_2 are random numbers within (0,1) and updated in each iteration. In this way, the opposite solution is built, and the unpredictability of the exploration is increased. After this step, a dynamic logarithmic spiral space between modified X_{op} and X_{best} is constructed in each iteration using the following description:

$$X_{t+1} = \left|X_{best} - X_{op}\right| \times e^{bl} \times \cos(2\pi l) + X_{best} \tag{9}$$

where X_{t+1} is the position vector of X at the moment of $t+1$, l is a random value within $[-1, 1]$ and determines how much the X_{t+1} is close to the X_{best} whereas a spiral shape is constructed for $b = 1$. Once the above definition is completed, random exploration is performed by the proposed algorithm as the last step. It is worth noting that the value of l has a significant role as it controls the exploration activities of the search agents for the entire logarithmic spiral space since $l = -1$ means the agent is within the closest position to the X_{best} whereas the farthest position is indicated by $l = 1$. Considering this significance, each of the agents of the HGS algorithm was assigned different l values in each iteration using the definition of $l = 2 \times rand - 1$ where *rand* denotes a random number within $(0, 1)$.

The proposed algorithm provides the following advantages. Firstly, it reduces the exploration space significantly as the constructed logarithmic spiral space is smaller than the entire exploration space. Secondly, more promising regions are considered for performing the exploration compared to the OBL scheme. Therefore, the proposed LsOBL-HGS algorithm maintains the diversity of exploration areas within a limited time and prevents the early convergence of the original form of the HGS algorithm.

4. Experimental results on recent benchmark functions

4.1. CEC2017 benchmark functions and compared algorithms

Twenty-nine benchmark functions from the CEC2017 test suite (Awad et al., 2016) were used for this study in order to perform the initial statistical assessment. Those benchmark functions provide a good platform for the performance assessment of the algorithms as they are challenging problems. In terms of comparative evaluation, the performance of the proposed LsOBL-HGS algorithm was assessed against other metaheuristic algorithms of grey wolf optimizer (GWO) (Mirjalili et al., 2014) as it is one of the most cited metaheuristic algorithms, along with Harris hawks optimization (HHO) (Heidari et al., 2019) and Aquila optimizer (AO) (Abualigah et al., 2021) algorithms as the latter ones are the recently reported and competitive algorithms. Besides, the original version of the HGS (Yang et al., 2021) algorithm was also used for making comparisons. All the algorithms were used with their default parameter values along with a population size of 50 and a total iteration number of 1,000. In addition, all the algorithms were run 30 times.

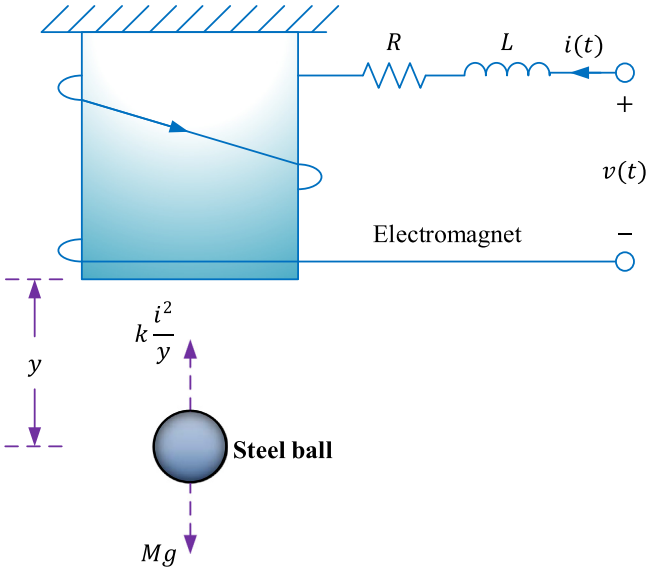


Fig. 2. Representation of magnetic ball suspension system.

4.2. Statistical performance

The CEC2017 test suite includes both unimodal (F01, F03) and multimodal (F04 - F10) functions which are good tools to assess the exploitation and exploration abilities of the algorithms. Apart from the latter forms, the CEC2017 test suite also includes hybrid (F11 – F20) and composition (F21 – F30) functions which are more challenging for test functions. Table 1 lists the comparative results on those functions in terms of the statistical performance criteria of mean and standard deviation (Std). The numerical values in Table 1 clearly show that the proposed LsOBL-HGS has better statistical performance than the compared ones.

5. Mathematical modeling of magnetic ball suspension system

The changing current passing through the coil of an electromagnet causes the field strength to change which makes the suspension of a ferromagnetic ball feasible. Fig. 2 provides a schematic representation of such a system. However, it is not easy to control this system because of its nonlinear and unstable nature. A feedback control system can be employed to address the latter issue, considering the dynamic behavior of the system.

The following Eq. (10) defines the net force acting on the ball (Golnaraghi and Kuo, 2017) where k, g, and M denote the electromagnet coefficient, the gravitational acceleration, and the mass of the ball, respectively.

$$M\frac{d^2y(t)}{dt^2} = M \cdot g - k\frac{i^2(t)}{y(t)} \tag{10}$$

In the latter definition, $y(t)$ stands for the position of the ball. The input voltage, $v(t)$ and the current, $i(t)$ of the coil can be explained with the following form where R and L denote the winding resistance and inductance, respectively.

$$v(t) = R \cdot i(t) + L\frac{di(t)}{dt} \tag{11}$$

The following linearized set of equations can be obtained where A^* and B^* are the coefficient matrices as shown in Eq. (12) (Golnaraghi and Kuo, 2017):

$$A^* = \begin{bmatrix} 0 & 1 & 0 \\ \frac{g}{x_{10}} & 0 & -2\sqrt{\frac{k \cdot g}{M \cdot x_{10}}} \\ 0 & 0 & -\frac{R}{L} \end{bmatrix}, B^* = \begin{bmatrix} 0 \\ 0 \\ 1/L \end{bmatrix} \tag{12}$$

Table 2 lists the parameters and the corresponding values of the magnetic ball suspension system which is considered in the present paper (Golnaraghi and Kuo, 2017).

5.1. Analysis of the system without a controller

The following transfer function can be obtained for the magnetic ball suspension system by adopting the related values for the listed parameters given in Table 2 and considering the equilibrium point of $y_0(t) = 0.5m$.

$$G(s) = C^*(sI - A^*)^{-1}B^* = [1 \quad 0 \quad 0](sI - A^*)^{-1}B^* = -\frac{885.9}{s^3 + 100s^2 - 19.62s - 1962} \tag{13}$$

The pole/zero map and the open-loop step response of the system, provided in Fig. 3, can be obtained using Eq. (13). One of the poles of the system is located in the right half-plane; it implies the unstable nature of the system which is also confirmed with the open-loop response of the system.

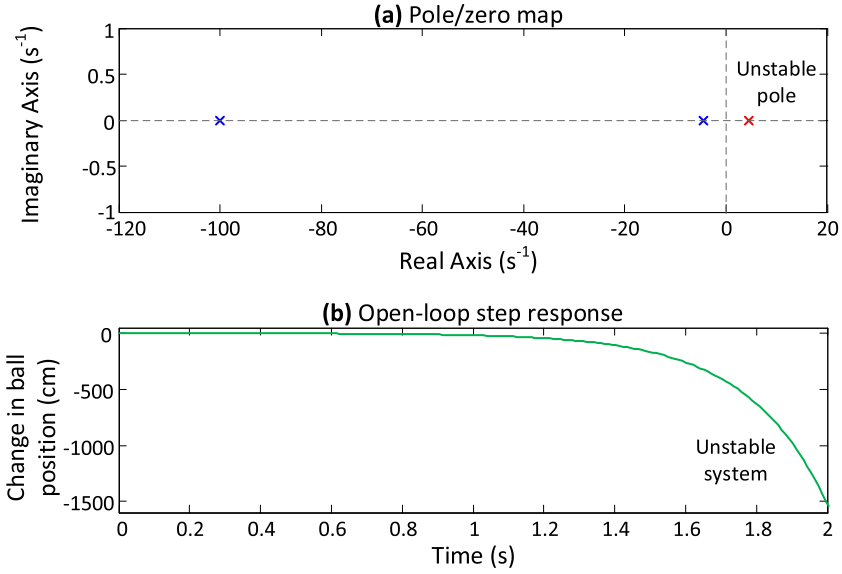


Fig. 3. Pole/zero map and open-loop step response of the system.

5.2. FOPID controller and its application to the system

Due to the availability of the fractional orders of λ and μ, a FOPID controller is a more advanced version of a PID controller and can provide more capability than that of a PID controller. The transfer function of a FOPID controller is defined as follows (Ekinci et al., 2020):

$$G_{FOPID}(s) = K_p + \frac{K_i}{s^{\lambda}} + K_d s^{\mu} \tag{14}$$

where K_p, K_i, K_d, λ, and μ are proportional gain, integral gain, derivative gain, fractional integral order, and fractional derivative order, respectively. Fig. 4 illustrates the block diagram of a FOPID controlled magnetic ball suspension system.

The closed-loop transfer function provided in Eq. (15) can be obtained for the magnetic ball suspension system by using the block diagram given above in Fig. 4.

Table 2
The system parameters and their values.

Parameter	Value
R(Winding resistance)	1 Ω
M(Ball mass)	1 kg
k(Proportional constant)	1 kg-m^2/A^2-s^2
L(Winding inductance)	0.01H
g(Gravitational acceleration)	9.81 m/s^2

$$CLTF(s) = \frac{G_{FOPID}(s)\cdot G(s)}{1 + G_{FOPID}(s)\cdot G(s)} = \frac{-885.9(K_d s^{\lambda+\mu} + K_p s^{\lambda} + K_i)}{(s^3 + 100s^2 - 19.62s - 1962)s^{\lambda} - 885.9(K_d s^{\lambda+\mu} + K_p s^{\lambda} + K_i)} \tag{15}$$

6. Problem definition and application of proposed LsOBL-HGS algorithm to the magnetic ball suspension system

The objective function, ZLG (Izci et al., 2022c), was adopted in this paper as the performance index since it is widely employed. This objective function is given with the following form where e_{ss} is the steady-state error, $\%OS$ is the percent overshoot, t_r is the rise time and t_s is the settling time.

$$F = (1 - e^{-\varphi}) \times \left(\frac{\%OS}{100} + e_{ss}\right) + e^{-\varphi} \times (t_s - t_r) \tag{16}$$

φ, the weighting parameter, was set to 1 (Ekinci et al., 2020) for this study. The block diagram provided in Fig. 5 illustrates the implementation of the proposed LsOBL-HGS algorithm to tune the FOPID controlled magnetic ball suspension system. The population size was chosen as 25 whereas the total iteration number (t_{max}) as 50. The algorithm performed the optimization for 30 runs. Apart from the latter values, the limits for the parameters of the FOPID controller were chosen as $-100 \le K_p, K_i, K_d \le 0$ and $0 < \lambda, \mu < 2$ (Demirören et al., 2021) for this study. Meanwhile, the controller parameters may be within negative values for some physical systems (Demirören et al., 2021) as is the case here.

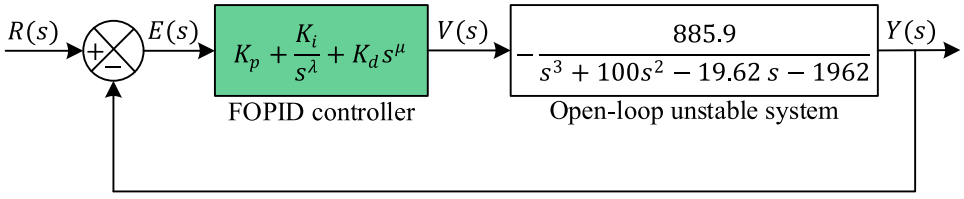


Fig. 4. Block diagram of the FOPID controlled system.

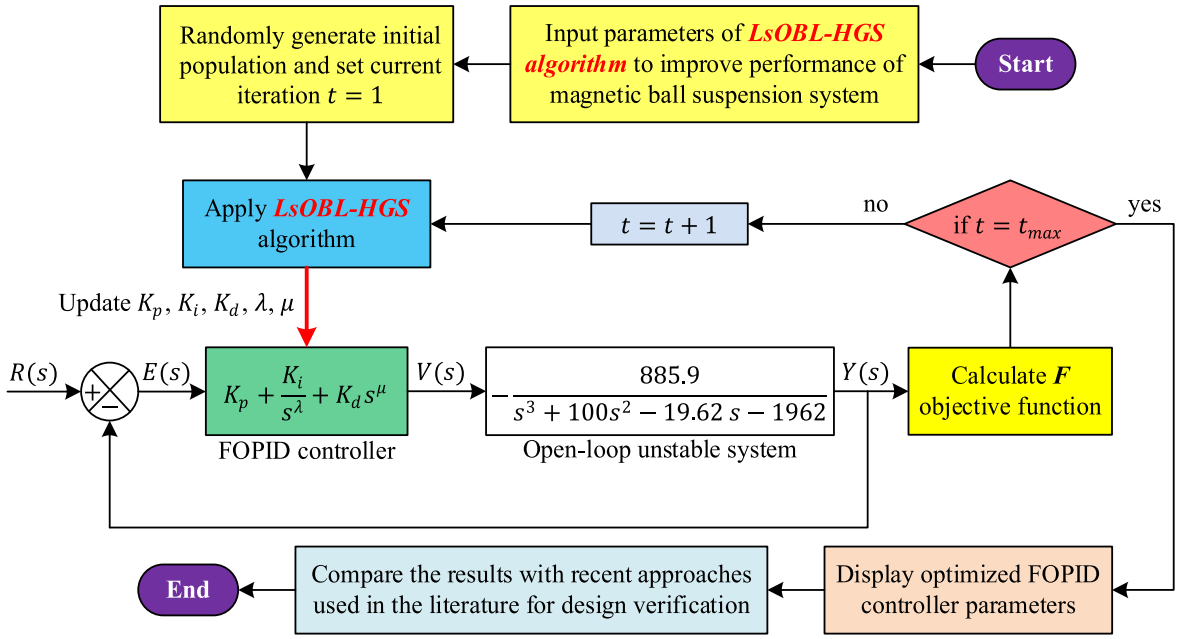


Fig. 5. Design of LsOBL-HGS based FOPID controller for the system.

7. Comparison with recently reported methods

7.1. Compared algorithms and their transfer functions

The performance of the LsOBL-HGS algorithm based FOPID controller for magnetic ball suspension was assessed comparatively using existing methods of artificial electric field algorithm based FOPID controller (AEF/FOPID) (Demirören et al., 2021), artificial bee colony algorithm based FOPID (ABC/FOPID) (Demirören et al., 2021), and atom search optimization based FOPID controller (ASO/FOPID) (Demirören et al., 2021). Table 3 lists those algorithms and the best-obtained values for the gain parameters and fractional orders of the FOPID controller.

Substituting those parameters into Eq. (15) would yield the closed-loop transfer functions (*CLTF*) of the magnetic ball suspension system given in Eqs. (17) - (21) for LsOBL-HGS, HGS, AEF, ASO, and ABC algorithms based FOPID controllers, respectively.

7.2. Transient response

The transient response-related performance indicators are demonstrated in Table 4. Besides, Fig. 6 provides the illustrative step responses of the LsOBL-HGS, HGS, AEF, ASO, and ABC algorithms based on FOPID controllers. The provided numerical and illustrative results show that the proposed LsOBL-HGS algorithm-based FOPID controller reaches less values of the related performance indicators, thus, clearly indicating a better time response profile of the proposed LsOBL-HGS algorithm based FOPID controller for the magnetic ball suspension system.

7.3. Frequency response

The numerical values for the frequency response-related performance indicators are listed in Table 5 for LsOBL-HGS, HGS, AEF, ASO, and ABC algorithms based FOPID controllers. Besides, Fig. 7

$$CLTF_{LsOBL-HGS}(s) = \frac{2795.5s^{2.1074} + 87557s^{0.8175} + 67283}{s^{3.8175} + 100s^{2.8175} + 2795.5s^{2.1074} - 19.62s^{1.8175} + 85595s^{0.8175} + 67283} \tag{17}$$

$$CLTF_{HGS}(s) = \frac{2194.2s^{2.2485} + 74027s^{0.9202} + 73038}{s^{3.9202} + 100s^{2.9202} + 2194.2s^{2.2485} - 19.62s^{1.9202} + 72065s^{0.9202} + 73038} \tag{18}$$

$$CLTF_{AEF}(s) = \frac{3201.5s^{2.1308} + 64547s^{0.9812} + 71783}{s^{3.9812} + 100s^{2.9812} + 3201.5s^{2.1308} - 19.62s^{1.9812} + 62585s^{0.9812} + 71783} \tag{19}$$

$$CLTF_{ASO}(s) = \frac{2406.6s^{2.0443} + 43853s^{0.8845} + 61973}{s^{3.8845} + 100s^{2.8845} + 2406.6s^{2.0443} - 19.62s^{1.8845} + 41891s^{0.8845} + 61973} \tag{20}$$

Table 3
Obtained FOPID controller parameters.

Parameter	LsOBL-HGS	HGS	AEF	ASO	ABC
K_p	−98.8349	−83.5623	−72.8609	−49.5017	−83.7975
K_i	−75.9496	−82.4457	−81.0298	−69.9558	−77.3375
K_d	−3.1556	−2.4768	−3.6139	−2.7166	−5.0983
λ	0.8175	0.9202	0.9812	0.8845	0.9905
μ	1.2899	1.3283	1.1496	1.1598	1.0293

Table 4
Comparison of percent overshoot, rise time and settling time.

Performance indicator	LsOBL-HGS	HGS	AEF	ASO	ABC
Overshoot (%)	12.7854	14.7983	17.1741	21.1222	27.8227
Rise time (s)	0.0208	0.0244	0.0257	0.0328	0.0246
Settling time (s)	0.2849	0.3087	0.3300	0.3562	0.3448

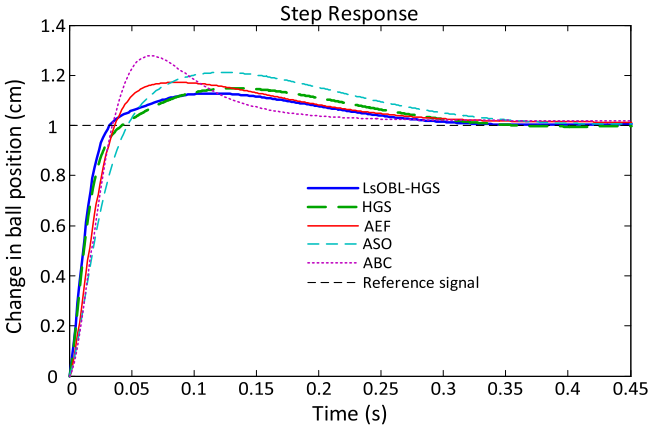


Fig. 6. Comparison of step responses.

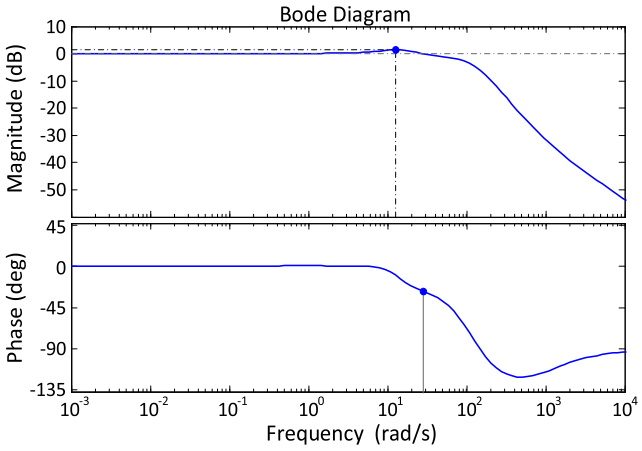


Fig. 7. Bode diagram of LsOBL-HGS based FOPID controlled system.

shows the Bode plot of the FOPID controlled magnetic ball suspension system tuned by the LsOBL-HGS algorithm. The comparative numerical results show that the LsOBL-HGS algorithm-based FOPID controller provides the most stable behavior for a magnetic ball suspension system in terms of frequency response.

7.4. Effect of the noise signal

The performance of the proposed LsOBL-HGS algorithm-based FOPID controller was also comparatively assessed in terms of suppressing the effect of the noise signal. White Gaussian noise with an input signal power of $1W$ and signal-to-noise ratio (SNR) of $20dB$ was introduced as the measurement noise. Fig. 8 demonstrates the obtained comparative results in this regard. The proposed LsOBL-HGS algorithm-based FOPID controller provides the most optimal dynamic response and deals with the noise better compared to other compared algorithms for the magnetic ball suspension system as can be observed from the respective figures.

7.5. Robustness

Lastly, the parameters of R and L were separately changed within ranges of $\pm 5\%$ and $\pm 20\%$, respectively, in order to demonstrate the robustness of the proposed LsOBL-HGS algorithm based FOPID controlled magnetic ball suspension system comparatively. Table 6 provides the comparative results for FOPID controlled magnetic ball suspension systems designed by LsOBL-HGS, HGS, AEF, ASO, and ABC algorithms. From the demonstrated parametric uncertainties, the better ability of the proposed LsOBL-HGS algorithm can be clearly observed.

Table 5
Comparison of gain margin, phase margin, and bandwidth.

Performance indicator	LsOBL-HGS	HGS	AEF	ASO	ABC
Gain margin (dB)	Inf.	Inf.	Inf.	Inf.	Inf.
Phase margin (deg)	152.7340	152.1233	133.2568	134.5349	103.2657
Bandwidth (Hz)	99.4241	83.8238	73.7792	54.6252	75.3558

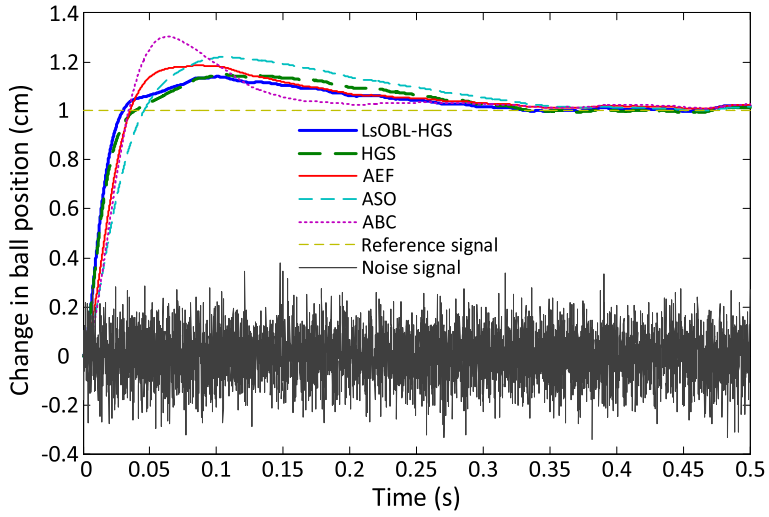


Fig. 8. Comparison of step responses in the case of measurement noise.

Table 6
Comparison of step responses under parameter uncertainties.

Parameter changes	Performance indicator	LsOBL-HGS	HGS	AEF	ASO	ABC
$R = 0.95$	Overshoot (%)	12.2011	14.1220	16.6556	20.2793	28.4027
	Rise time (s)	0.0198	0.0230	0.0455	0.0313	0.0411
	Settling time (s)	0.2804	0.3042	0.3272	0.3518	0.3225
$R = 1.05$	Overshoot (%)	13.3684	15.4708	15.7177	21.9624	27.2311
	Rise time (s)	0.0218	0.0260	0.0458	0.0343	0.0255
	Settling time (s)	0.2891	0.3129	0.3387	0.3604	0.3866
$L = 0.008$	Overshoot (%)	12.5253	14.5220	16.2963	20.4661	24.0178
	Rise time (s)	0.0210	0.0257	0.0258	0.0335	0.0244
	Settling time (s)	0.2886	0.3124	0.3346	0.3615	0.3416
$L = 0.012$	Overshoot (%)	13.0704	15.1044	19.1864	21.0597	31.9315
	Rise time (s)	0.0210	0.0242	0.0259	0.0486	0.0251
	Settling time (s)	0.2810	0.3048	0.3252	0.3516	0.3472

8. Conclusion

The construction of a novel augmented HGS algorithm using a logarithmic spiral OBL scheme has been discussed in this paper. The novel LsOBL-HGS algorithm has been proposed as an efficient tool both for function optimization and FOPID controller design for the magnetic ball suspension system. Evaluations against benchmark functions from the CEC2017 test suite have shown an increased performance of the proposed LsOBL-HGS algorithm compared to the original form of HGS, GWO, HHO, and AO algorithms. Similarly, the comparative performance of the proposed LsOBL-HGS based FOPID controlled magnetic ball suspension system has been demonstrated using several analyses. The proposed system has demonstrated better performance compared to other state-of-the-art methods of AEF, ASO, and ABC algorithms based FOPID controllers reported for magnetic ball suspension system as the transient response-related parameters have been improved by then 13% and the bandwidth by more than 34% compared to the best-reported approach used for comparisons.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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