

## MOFPA-BASED PIDA CONTROLLER DESIGN OPTIMIZATION FOR ELECTRIC FURNACE TEMPERATURE CONTROL SYSTEM

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**ABSTRACT.** *The flower pollination algorithm (FPA) was developed and proposed as one of the nature-inspired population-based metaheuristic optimization techniques for solving optimization problems. In this paper, the enhanced version of the original FPA called the modified flower pollination algorithm (MoFPA) is presented to improve the search performance. The switching probability of the original FPA used for selection between local and global pollinations is changed from the fixed manner to the random manner. The proposed MoFPA is tested against five benchmark optimization problems compared with the original FPA. Then, the proposed MoFPA is applied to the proportional-integral-derivative-accelerated (PIDA) controller design optimization for the electric furnace temperature control system. System responses obtained by the PIDA controller designed by the MoFPA will be compared with those obtained by the PID controller designed by the MoFPA. As results, the proposed MoFPA performs more efficient and more robust in global optimum finding of five selected benchmark optimization problems with higher success rates than the original FPA. In addition, the PIDA controller designed by the proposed MoFPA can provide the very satisfactory tracking and regulating responses of the electric furnace temperature control system superior to the PID controller.*

**Keywords:** Modified flower pollination algorithm, PIDA controller, Electric furnace temperature control system, Constrained optimization problem

**1. Introduction.** Over the last few decades, the nature-inspired metaheuristic algorithms have become very popular in a wide range of real-world applications including control system engineering problems. This is due to their success in finding global solutions for complex problems, especially the NP-complete problems [1-4]. Acceptation of the metaheuristic algorithms is because they rely on rather simple concepts and easy to implement based on randomly searching approach. They do not require gradient information and can escape local entrapments. Finally, they can be applied in a wide range of problems covering different disciplines [1-4]. Following the literature, most nature-inspired metaheuristic algorithms are developed by mimicking biological or physical phenomena. They can be grouped in four main categories, i.e., (i) evolution-based metaheuristic algorithms, (ii) physics-based metaheuristic algorithms, (iii) bio-swarm-based metaheuristic algorithms and (iv) human-based metaheuristic algorithms.

The most popular evolution-based algorithms are genetic algorithms (GA) [5] and differential evolution (DE) [6]. The most well-known physics-based algorithms are simulated annealing (SA) [7] and big-bang big-crunch (BBBC) [8]. Many bio-swarm-based algorithms are most popular, for instance, particle swarm optimization (PSO) [9], ant colony optimization (ACO) [10], bat-inspired algorithm (BA) [11], firefly algorithm (FA) [12],

hunting search (HS) [13], grey wolf optimizer (GWO) [14], whale optimization algorithm (WOA) [15], cuckoo search (CS) [16], flower pollination algorithm (FPA) [17] and monarch butterfly optimization (MBO) [18]. For the last group, the most popular human-based algorithms are tabu search (TS) [19], harmony search (HS) [20], brainstorm optimization algorithm (BOA) [21] and spiritual search (SS) [22].

The FPA was firstly proposed by Yang in 2012 [17] for solving both continuous and combinatorial, single-objective and multi-objective optimization problems. The FPA algorithm imitates the pollination behavior of flowering plants. Optimal plant reproduction strategy involves the survival of the fittest as well as the optimal reproduction of plants in terms of numbers. These factors represent the fundamentals of the FPA and are optimization-oriented. The FPA algorithm was proved for the global convergent property [23]. Since 2012, the FPA has shown superiority to other metaheuristic algorithms in solving various real-world engineering problems, such as economic/emission dispatch, reactive power dispatch, optimal power flow, solar PV parameter estimation, load frequency control, wireless sensor networks, linear antenna array optimization, frames and truss systems, structure engineering design, multilevel image thresholding, travelling transportation problem, control system design and model identification. The state-of-the-art developments and significant applications of the FPA have been reviewed and reported [24,25]. From literature review, the FPA is one of the most popular and efficient metaheuristic algorithms.

Recently, many variants of FPA have been developed by modification, hybridization, and parameter-tuning manners in order to cope with the complex nature of optimization problems [25]. One of the modified flower pollination algorithms is called the MFPA [26]. The MFPA hybridized the original FPA with the clonal selection algorithm (CSA) in order for generating some elite solutions. The binary flower pollination algorithm (BFPA) was developed for solving discrete and combinatorial optimization problems [27]. Another significant modification was proposed as the modified global FPA (mgFPA) [28]. The mgFPA was designed to better utilize features of existing solutions through extracting its characteristics, and direct the exploration process towards specific search areas [28].

In this paper, the novel enhanced version of the original FPA named the modified flower pollination algorithm (MoFPA) is proposed. The switching probability of the original FPA used for selection between local and global pollinations is changed from the fixed manner to the random manner. The proposed MoFPA is tested against five benchmark optimization problems compared with the original FPA in order to perform its effectiveness. The proposed MoFPA is then applied to designing the proportional-integral-derivative-accelerated (PIDA) controller for the electric furnace temperature control system. This paper consists of five sections. After an introduction presented in Section 1, the rest of the paper is arranged as follows. The original FPA and the proposed MoFPA algorithms as well as performance evaluation of the MoFPA against five benchmark optimization problems are described in Section 2. Application of the MoFPA to the PIDA controller design optimization for the electric furnace temperature control system is given in Section 3. Results and discussions are illustrated in Section 4, while the conclusions are followed in Section 5.

**2. Modified Flower Pollination Algorithm.** In this section, the algorithm of the original FPA is briefly described. Then, the algorithm of the proposed MoFPA is elaborately detailed. Also, the performance evaluation of the MoFPA is performed as follows.

**2.1. Original FPA.** In nature, the objective of the flower pollination is the survival of the fittest and optimal reproduction of flowering plants. Pollination in flowering plants

can take two major forms, i.e., biotic and abiotic [29]. About 80-90% of flowering plants belong to biotic pollination. Pollen is transferred by a pollinator such as bees, birds, insects and animals. About 10-20% remaining of pollination takes abiotic such as wind and diffusion in water. Pollination can be achieved by self-pollination or cross-pollination [30,31]. Self-pollination is the fertilization of one flower from pollen of the same flower or different flowers of the same plant. Self-pollination usually occurs at short distance without pollinators. It is regarded as the local pollination. Cross-pollination occurs when pollen grains are moved to a flower from another plant. The process happens with the help of biotic or abiotic agents as pollinators. Biotic, cross-pollination may occur at long distance with biotic pollinators. It is regarded as the global pollination. Biotic pollinators behave Lévy flight behavior [32] with jump or fly distance steps obeying a Lévy flight distribution. The original FPA, proposed in 2012 by Yang [17], was developed by the characteristics of the pollination process, flower constancy and pollinators' behavior.

In original FPA algorithms, a solution  $\mathbf{x}_i$  is equivalent to a flower and/or a pollen gamete. For global pollination, flower pollens are carried by pollinators. With Lévy flight, pollens can travel over a long distance as expressed in (1), where  $\mathbf{g}^*$  is the current best solution found among all solutions at the current generation (iteration)  $t$ , and  $L$  stands for the Lévy flight that can be approximated by (2), while  $\Gamma(\lambda)$  is the standard gamma function. The local pollination can be represented by (3), where  $\mathbf{x}_j$  and  $\mathbf{x}_k$  are pollens from the different flowers of the same plant species, while  $\varepsilon$  stands for random drawn from a uniform distribution as stated in (4). The switch probability  $p$  is used to switch between global pollination and local pollination. The algorithm of the original FPA can be represented by the flow diagram shown in Figure 1. Yang reported that the best parameters for most applications are the number of flowers  $n = 25-50$  and the switching probability  $p = 0.2-0.25$  [17,24,25].

$$\mathbf{x}_i^{t+1} = \mathbf{x}_i^t + L (\mathbf{x}_i^t - \mathbf{g}^*) \quad (1)$$

$$L \approx \frac{\lambda \Gamma(\lambda) \sin(\pi \lambda / 2)}{\pi} \frac{1}{s^{1+\lambda}}, \quad (s \gg s_0 > 0) \quad (2)$$

$$\mathbf{x}_i^{t+1} = \mathbf{x}_i^t + \varepsilon (\mathbf{x}_j^t - \mathbf{x}_k^t) \quad (3)$$

$$\varepsilon(\rho) = \begin{cases} 1/(b-a), & a \leq \rho \leq b \\ 0, & \rho < a \text{ or } \rho > b \end{cases} \quad (4)$$

**2.2. Proposed MoFPA.** Regarding to flowering plants in nature, pollination ability of the flowering plant between cross-pollination via biotic pollinator and self-pollination via abiotic pollinator depends on the nature of flowering plant species [30,31]. Once such the behavior is conducted in order to perform algorithms, it should be random manner within the particular interval instead of fixed value manner as appearing in the original FPA algorithm [17]. With this concept, the new developed algorithm can reach the optimality faster. The proposed MoFPA algorithm, the new enhanced version of the original FPA, employs the randomly switching probability for selection between local and global pollinations. This leads the opportunity of the global finding of the proposed MoFPA algorithm according to the flower pollination behavior in nature. By this concept and new motivation, the random process of pollination remains unchanged, i.e.,  $rand \in [0, 1]$ , but the fixed value of the switching probability  $p = 0.2$  will be changed to the randomly switching probability  $randp \in [0, p_{max}]$ ,  $p_{max} \leq 0.5$ , regarding to the natural flower pollination behavior.

Referring to the original FPA algorithm in Figure 1, the condition of selection between local and global pollinations is  $rand > p$ , where  $rand \in [0, 1]$  is random number drawn from a uniform distribution and  $p$  is a fixed value. If  $rand > p$ , the global pollination will

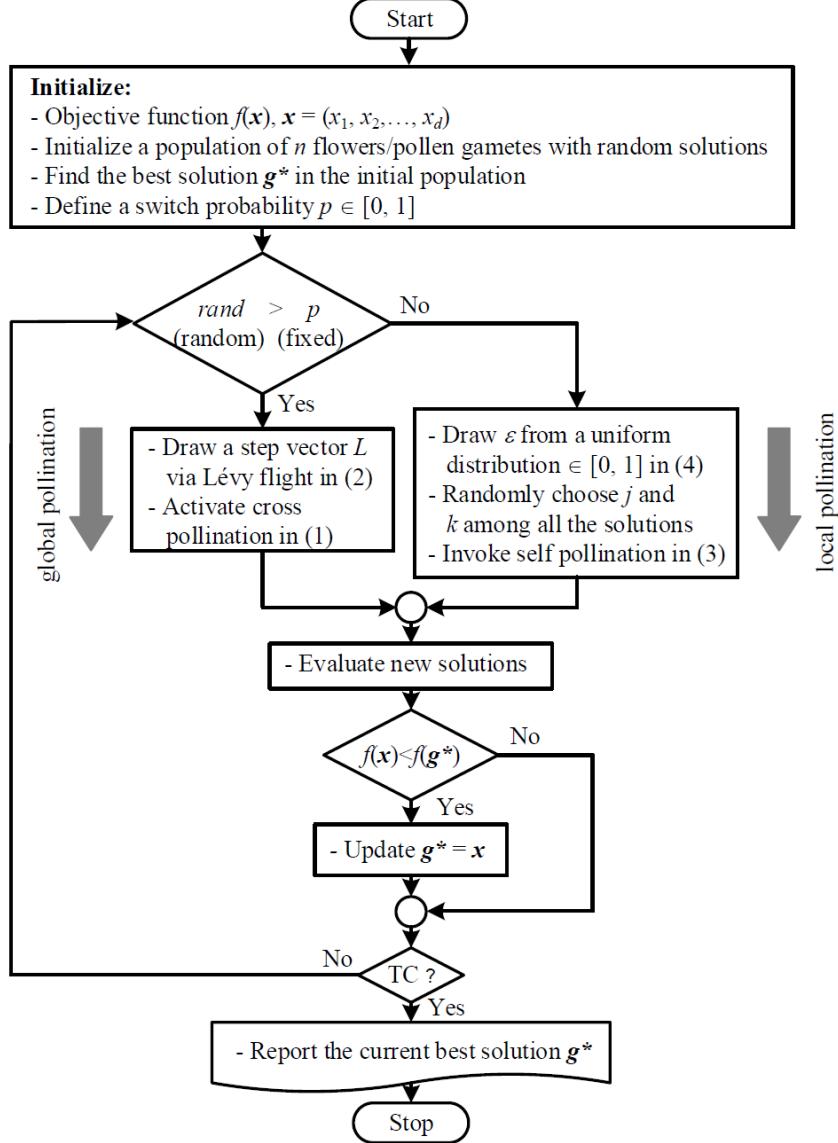


FIGURE 1. Flow diagram of the original FPA

be activated as shown in Figure 2(a). Otherwise, the local pollination will be invoked. The algorithm of the proposed MoFPA can be modified by the flow diagram of the original FPA as shown in Figure 1. The condition of selection between local and global pollinations is changed to  $rand > randp$ , where  $rand \in [0, 1]$  and  $randp \in [0, p_{\max}]$  are random numbers drawn from a uniform distribution. With a new selecting condition, if  $rand > randp$ , the global pollination will be activated as shown in Figure 2(b). Otherwise, the local pollination will be invoked. From this modification, the mathematical relations in (1)-(4) of the original FPA will be conducted in the proposed MoFPA. The algorithm of the proposed MoFPA can be represented by the flow diagram shown in Figure 3.

**2.3. Performance evaluation.** To perform its performance, the proposed MoFPA will be tested against five selected benchmark optimization problems [33,34]. All selected benchmark optimization problems are considered as the 2D-surface optimization problems as follows.

(i) Sinusoid function (SF) is expressed as  $f_1(x, y)$  in (5). It has a global minimum  $f(x^*, y^*) = -18.5547$  at optimal solutions  $(x^*, y^*) = (9.039, 8.668)$ . The SF's surface is

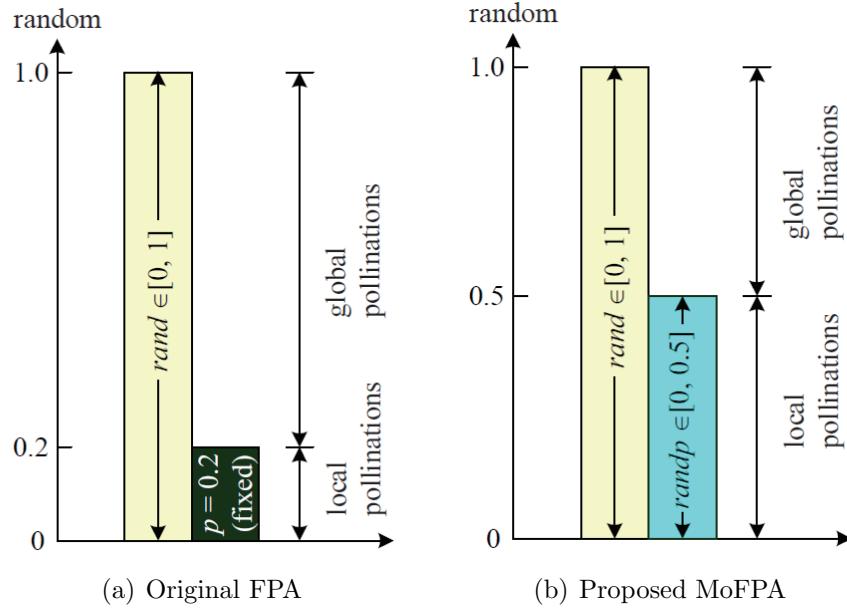


FIGURE 2. Selecting conditions between local and global pollinations

shown as an example in Figure 4.

$$f_1(x, y) = x \sin(4x) + 1.1y \sin(2y), \quad 0 \leq x, y \leq 10 \quad (5)$$

(ii) Bohachevsky function (BF) is stated as  $f_2(x, y)$  in (6). It has a global minimum  $f(x^*, y^*) = 0$  at optimal solutions  $(x^*, y^*) = (0, 0)$ .

$$f_2(x, y) = x^2 + 2y^2 - 0.3 \cos(3\pi x) - 0.4 \cos(4\pi y) + 0.7, \quad -50 \leq x, y \leq 50 \quad (6)$$

(iii) Rastrigin function (RF) is expressed as  $f_3(x, y)$  in (7). It has a global minimum  $f(x^*, y^*) = 0$  at optimal solutions  $(x^*, y^*) = (0, 0)$ .

$$f_3(x, y) = 20 + (x^2 - 10 \cos(2\pi x)) + (y^2 - 10 \cos(2\pi y)), \quad -5.12 \leq x, y \leq 5.12 \quad (7)$$

(iv) Griewank function (GF) is shown as  $f_4(x, y)$  in (8). It has a global minimum  $f(x^*, y^*) = 0$  at optimal solutions  $(x^*, y^*) = (0, 0)$ .

$$f_4(x, y) = \frac{1}{4000} (x^2 + y^2) - \cos(x) \cos\left(y/\sqrt{2}\right) + 1, \quad -600 \leq x, y \leq 600 \quad (8)$$

(v) Michaelwicz function (MF) is expressed as  $f_5(x, y)$  in (9). It has a global minimum  $f(x^*, y^*) = -1.8013$  at optimal solutions  $(x^*, y^*) = (2.20319, 1.57049)$ .

$$f_5(x, y) = -\sin(x) \sin(x^2/\pi)^{20} - \sin(y) \sin(2y^2/\pi)^{20}, \quad 0 \leq x, y \leq \pi \quad (9)$$

For comparison, both original FPA and MoFPA algorithms were coded by MATLAB version 2018b (License No.#40637337) run on Intel(R) Core(TM) i5-3470 CPU@3.60GHz, 4.0GB-RAM. Searching parameters of the original FPA are set according to recommendations of Yang [17], i.e., number of flowers  $n = 40$ , a switching probability  $p = 0.2$  (20%). For the proposed MoFPA, searching parameters are correspondingly set as  $n = 40$  and  $p_{max} = 0.5$  (50%). 100-trial runs are conducted for each algorithm so as to carry out meaningful statistical analysis. The algorithms will be terminated when the variations of function values are less than a given tolerance  $\delta \leq 10^{-5}$ . The results are summarized in Table 1, where the global optima are reached. The quantitative data in Table 1 are in the format of ANE  $\pm$  STD(PSR), where ANE is the average number of evaluations, STD is the standard deviation and PSR is percent success rate. From Table 1, it was found

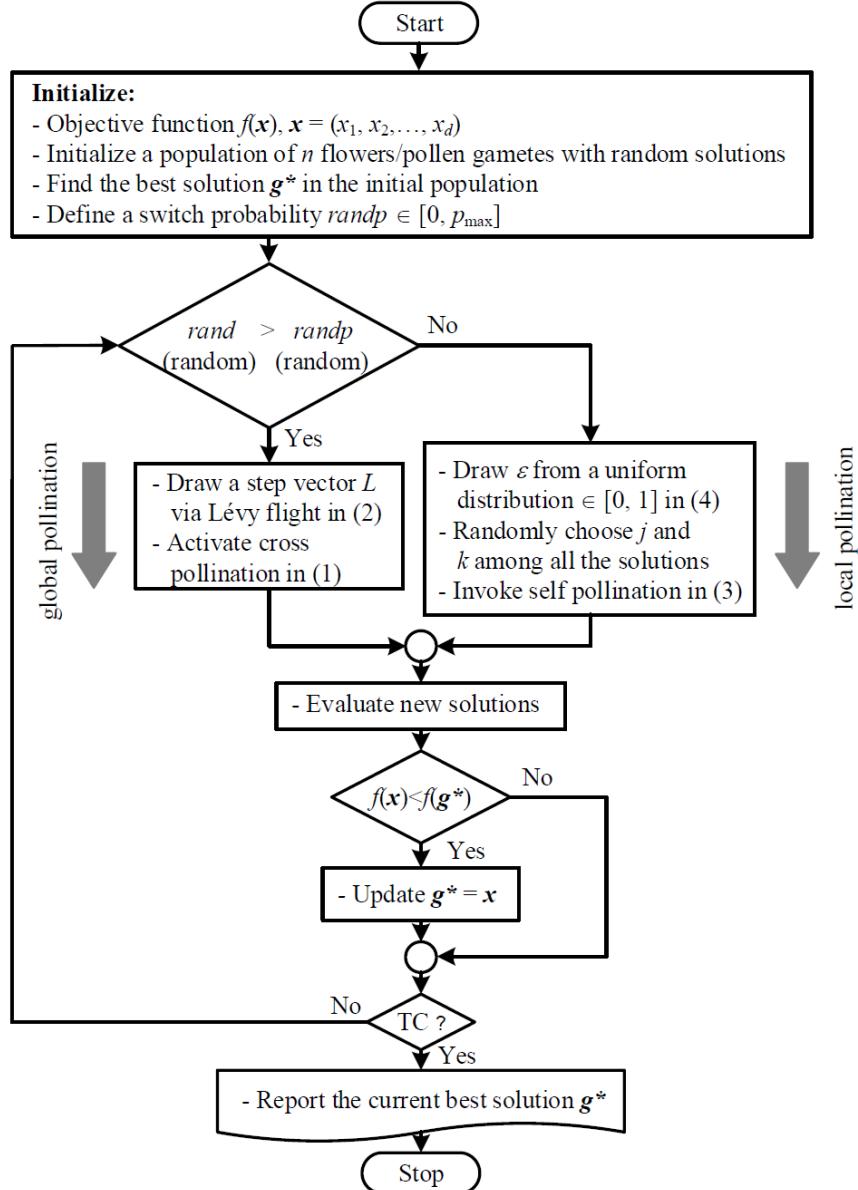


FIGURE 3. Flow diagram of the proposed MoFPA

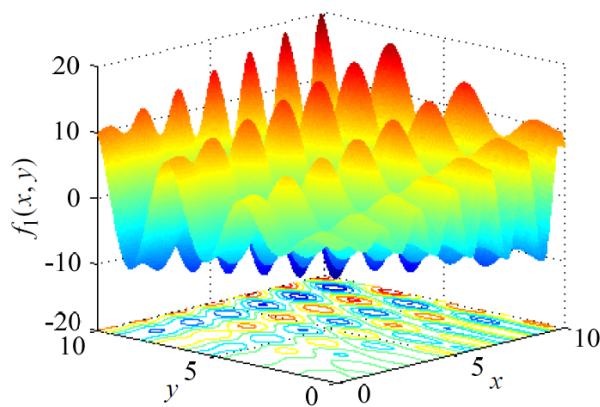


FIGURE 4. Surface of sinusoid function (SF)

TABLE 1. Result comparison between FPA and MoFPA

Entry	Test functions	Algorithms	
		Original FPA	Proposed MoFPA
(i)	SF, $f_1(x, y)$	$658 \pm 126(100\%)$	$426 \pm 103(100\%)$
(ii)	BF, $f_2(x, y)$	$782 \pm 224(100\%)$	$561 \pm 174(100\%)$
(iii)	RF, $f_3(x, y)$	$921 \pm 282(100\%)$	$732 \pm 156(100\%)$
(iv)	GF, $f_4(x, y)$	$1346 \pm 431(99\%)$	$928 \pm 274(100\%)$
(v)	MF, $f_5(x, y)$	$1025 \pm 365(100\%)$	$884 \pm 211(100\%)$

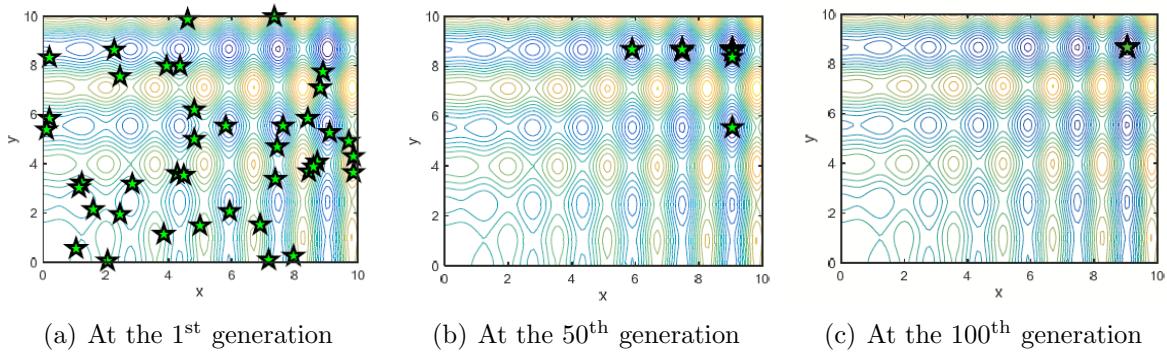


FIGURE 5. MoFPA movement for global optimal finding of sinusoid function (SF)

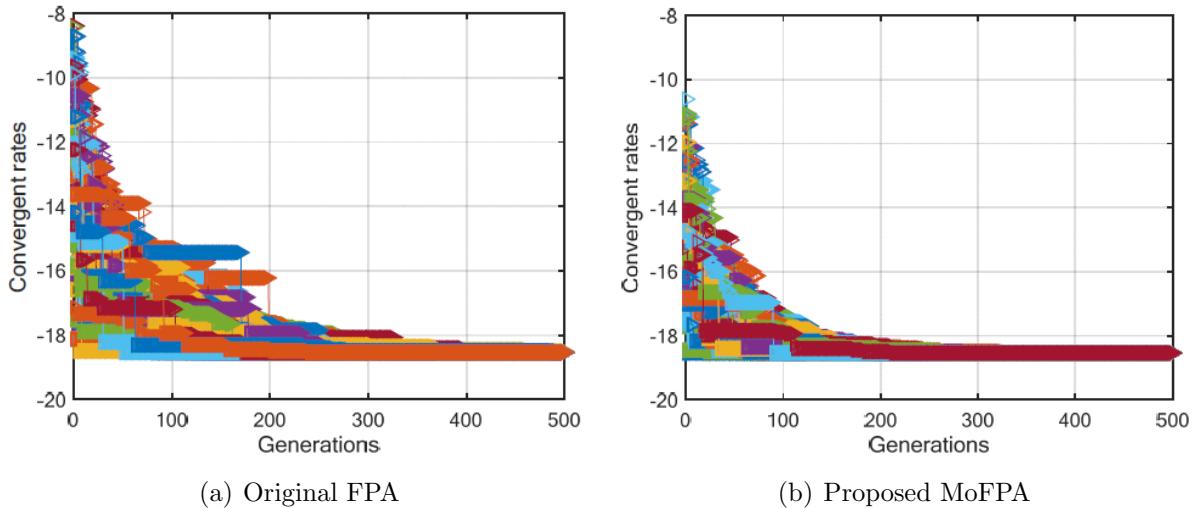


FIGURE 6. Convergent rates over 100-trial runs of the SF's solution finding

that the proposed MoFPA is more efficient in finding the global optima with faster (less average number of evaluations) and higher success rates superior to the original FPA. Figure 5(a), Figure 5(b) and Figure 5(c) show the results of the global optimal finding by the MoFPA against the SF function at the 1<sup>st</sup>, 50<sup>th</sup> and 100<sup>th</sup> generation, respectively.

The convergent rates over 100-trial runs of the SF's solution finding proceeded by the original FPA and the proposed MoFPA are shown in Figure 6(a) and Figure 6(b), respectively. It can be observed that the proposed MoFPA is more robust than the original FPA in global optimum finding.

**3. Application of MoFPA to PIDA Controller Design.** Application of the MoFPA to optimal PIDA controller design for the electric furnace temperature control system is performed in this section. The electric furnace temperature system operated under the PIDA feedback control loop is represented by the block diagram as shown in Figure 7, where  $G_p(s)$  and  $G_c(s)$  are the models of plant and controller, respectively. From Figure 7, the PIDA controller receives the error signal,  $E(s)$ , and produces the control signal,  $U(s)$ , to control the output response,  $C(s)$ , referring to the referent input,  $R(s)$ , and regulate the output response,  $C(s)$ , from the external disturbance signal,  $D(s)$ .

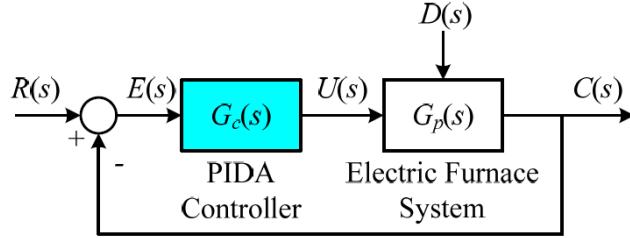


FIGURE 7. PIDA feedback control loop

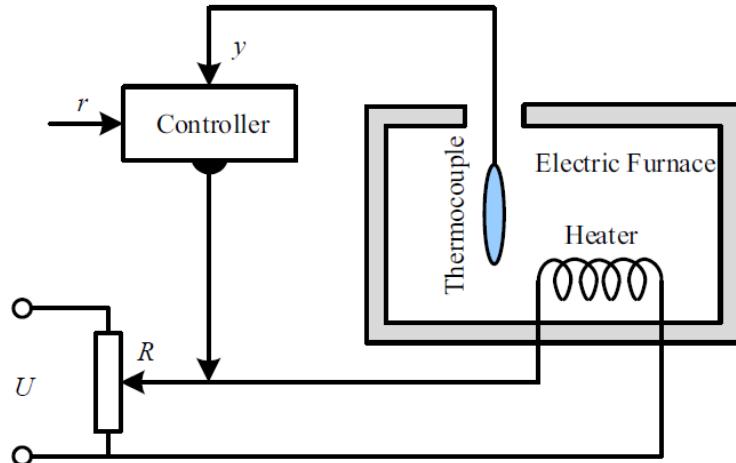


FIGURE 8. Electric furnace temperature system [35]

The schematic diagram of the electric furnace temperature system is shown in Figure 8 [35] consisting of electrical furnace, controller, thermocouple and heater in order to control the temperature in electrical furnace. Referring to Figure 8,  $r$  is input voltage,  $U$  is output voltage from controller,  $y$  is output voltage from thermocouple and  $R$  is armature resistance. The  $s$ -domain transfer function of the electric furnace temperature system  $G_p(s)$  was formulated as the second-order system plus time delay (SOSPD) [35] as given in (10). The time delay (or transport lag) in (10) can be approximated by the first-order Padé approximation stated in (11). Then, the  $s$ -domain transfer function of the electric furnace temperature system in (10) can be rewritten as expressed in (12). The model  $G_p(s)$  in (12) is then used as the plant model in the control loop shown in Figure 7.

$$G_p(s) = \frac{0.15}{s^2 + 1.1s + 0.2} e^{-1.5s} \quad (10)$$

$$e^{-1.5s} = \frac{1 - 0.75s}{1 + 0.75s} \quad (11)$$

$$G_p(s) = \frac{-0.1125s + 0.15}{0.75s^3 + 1.825s^2 + 1.25s + 0.2} \quad (12)$$

The PIDA controller, proposed by Jung and Dorf in 1996 [36], possesses the  $s$ -domain transfer function as stated in (13), where  $K_p$ ,  $K_i$ ,  $K_d$  and  $K_a$  are proportional, integral, derivative and accelerated gains, respectively. Referring to (13),  $d$  and  $e$  are poles of the PIDA controller. Once  $0 \ll d, e$ , the poles  $d, e$  can be neglected [36]. Therefore, the PIDA transfer function in (13) can be rewritten as expressed in (14). It can be observed that the PIDA controller possesses three arbitrary zeros and one pole at origin. If  $K_a$  in (14) is set as zero ( $K_a = 0$ ), the PIDA controller becomes the PID one [35-37].

$$G_c(s)|_{PIDA} = K_p + \frac{K_i}{s} + \frac{K_d s}{(s+d)} + \frac{K_a s^2}{(s+d)(s+e)} \quad (13)$$

$$G_c(s)|_{PIDA} = K_p + \frac{K_i}{s} + K_d s + K_a s^2 \quad (14)$$

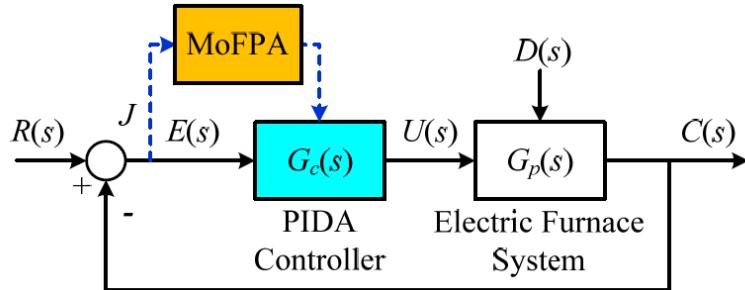


FIGURE 9. MoFPA-based PIDA controller design optimization framework

The MoFPA-based PIDA controller design optimization framework for the electric furnace temperature control system can be represented by the block diagram as shown in Figure 9. This framework is applied from the controller design optimization frameworks [38-40] based on the modern optimization. The objective function  $J$  is performed as sum-squared error between the reference temperature  $R(s)$  and the actual temperature  $C(s)$  stated in (15) to minimize the error  $E(s)$  between  $R(s)$  and  $C(s)$  according to the control system design context.  $J$  will be sent to the MoFPA block to be minimized by searching for the optimal values of  $K_p$ ,  $K_i$ ,  $K_d$  and  $K_a$  as the parameters of the PIDA controller within their particular boundaries or search spaces as shown in (16). In this work,  $J$  will be minimized according to the constrained functions as defined in (16), where  $t_r$  and  $t_{r\_max}$  are rise time and maximum rise time,  $M_p$  and  $M_{p\_max}$  are percent overshoot and maximum percent overshoot,  $t_s$  and  $t_{s\_max}$  are settling time and maximum settling time, and  $e_{ss}$  and  $e_{ss\_max}$  are steady-state error and maximum steady-state error, respectively. The constrained functions in (16) is performed by the time-domain design specification of the system of interest. Setting the constrained functions needs to meet the design specification and the possibility of the controller implementation.

$$\text{Minimize } J = \sum_{i=1}^N (R_i - C_i)^2 \quad (15)$$

$$\text{Subject to } \begin{aligned} t_r &\leq t_{r\text{-max}}, & M_p &\leq M_{p\text{-max}}, \\ t_s &\leq t_{s\text{-max}}, & e_{ss} &\leq e_{ss\text{-max}}, \\ K_{p\text{-min}} &\leq K_p \leq K_{p\text{-max}}, & K_{i\text{-min}} &\leq K_i \leq K_{i\text{-max}}, \\ K_{d\text{-min}} &\leq K_d \leq K_{d\text{-max}}, & K_{a\text{-min}} &\leq K_a \leq K_{a\text{-max}} \end{aligned} \quad \left. \right\} \quad (16)$$

**4. Results and Discussions.** To apply the proposed MoFPA for designing the optimal PIDA controller of the electric furnace temperature control system, the MoFPA algorithm was coded by MATLAB version 2018b (License No.#40637337) run on Intel(R) Core(TM) i5-3470 CPU@3.60GHz, 4.0GB-RAM. The searching parameters of MoFPA are set as follows:  $n = 40$  and  $p_{\max} = 0.5$  (50%). The objective function  $J$  in (15) is then conducted. From the preliminary study of this system, search spaces and constraint functions in (16) are then performed as given in (17). The maximum generation Max\_Gen = 500 is then set as the termination criteria (TC). 50-trial runs are conducted to find the optimal PIDA controller for the electric furnace temperature control system. For comparison with the PID controller,  $K_a$  in (14) and (16) will be set as zero.

$$\text{Subject to } \begin{aligned} t_r &\leq 4.5 \text{ sec.,} & M_p &\leq 10.0\%, \\ t_s &\leq 10.0 \text{ sec.,} & e_{ss} &\leq 0.01\%, \\ 0 &\leq K_p \leq 5.0, & 0 &\leq K_i \leq 1.0, \\ 0 &\leq K_d \leq 10.0, & 0 &\leq K_a \leq 1.5 \end{aligned} \quad \left. \right\} \quad (17)$$

$$G_c(s)|_{PID} = 3.55 + \frac{0.61}{s} + 3.85s \quad (18)$$

$$G_c(s)|_{PIDA} = 3.98 + \frac{0.66}{s} + 4.99s + 0.99s^2 \quad (19)$$

Once 50-trial runs of the search process were completed, the MoFPA can successfully provide the optimal PID and PIDA controllers for the electric furnace temperature control system as shown in (18) and (19), respectively. The convergent rates of the objective functions in (15) associated with inequality constraint functions in (17) proceeded by the MoFPA over 50-trial runs for PID and PIDA controllers design are plotted in Figure 10(a) and Figure 10(b), respectively.

The input-tracking (or command-following) and the load-regulating (or disturbance-rejecting) responses of the electric furnace temperature control system with the PIDA

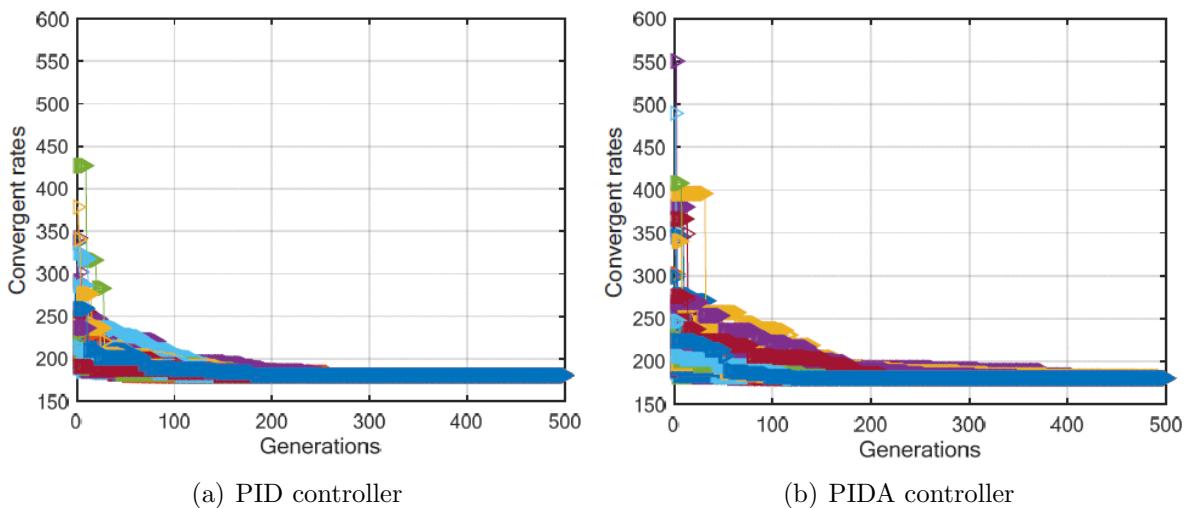


FIGURE 10. Convergent rates over 50-trial runs of controllers designed by MoFPA

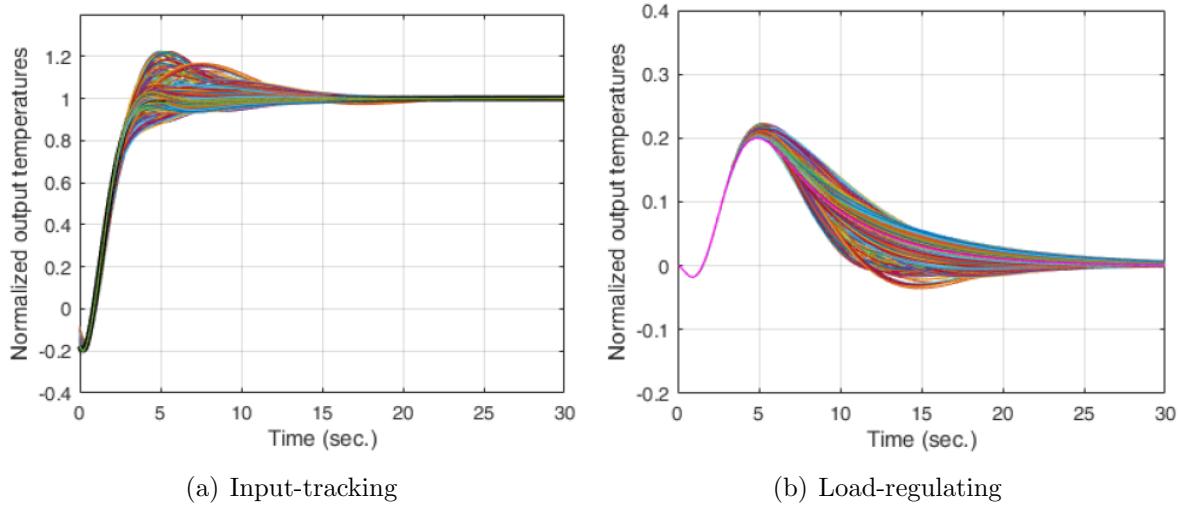


FIGURE 11. Responses of the electric furnace controlled system during PI-DA design process by MoFPA

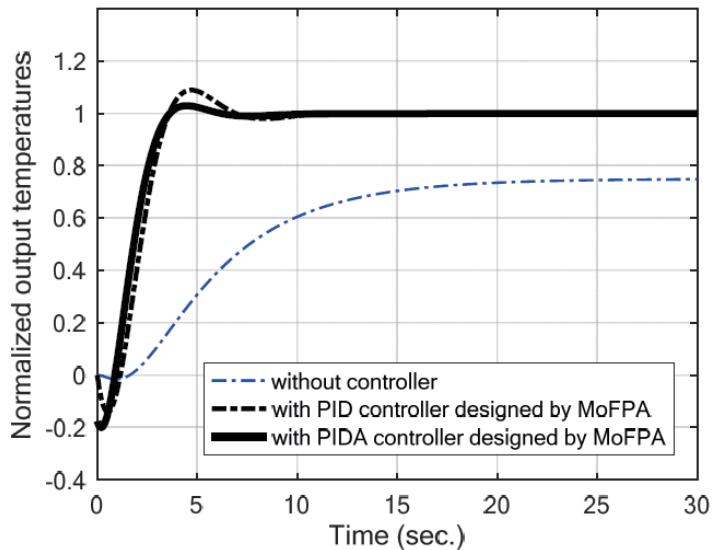


FIGURE 12. Input-tracking responses of the electric furnace temperature controlled system without and with PID and PIDA controllers optimized by MoFPA

controller during 500-generation design process proceeded by the proposed MoFPA are depicted in Figure 11(a) and Figure 11(b), respectively.

The input-tracking responses of the electric furnace temperature control system without controller, with PID controller in (18) and with PIDA controller in (19) designed by the MoFPA are depicted in Figure 12. Referring to Figure 12, the electric furnace temperature system without controller provides  $t_r = 14.56$  sec.,  $t_s = 20.12$  sec., without  $M_p$  and  $e_{ss} = 0.2520$  (25.20%). With PID controller, the input-tracking response of the electric furnace temperature control system yields  $t_r = 3.61$  sec.,  $t_s = 8.46$  sec.,  $M_p = 8.95\%$  and without  $e_{ss}$ . Finally, the input-tracking response of the electric furnace temperature control system with PIDA controller gives  $t_r = 3.61$  sec.,  $t_s = 5.18$  sec.,  $M_p = 2.95\%$  and without  $e_{ss}$ .

The load-regulating responses of the electric furnace temperature control system with PID controller in (18) and with PIDA controller in (19) designed by the MoFPA are plotted in Figure 13. From Figure 13, the electric furnace temperature control system with PID controller provides the maximum overshoot from regulating  $M_{p\_reg} = 22.75\%$  and recovering time from regulating  $t_{r\_reg} = 16.78$  sec. However, the load-regulating response of the electric furnace temperature control system with the PIDA controller gives  $M_{p\_reg} = 20.01\%$  and  $t_{r\_reg} = 16.49$  sec.

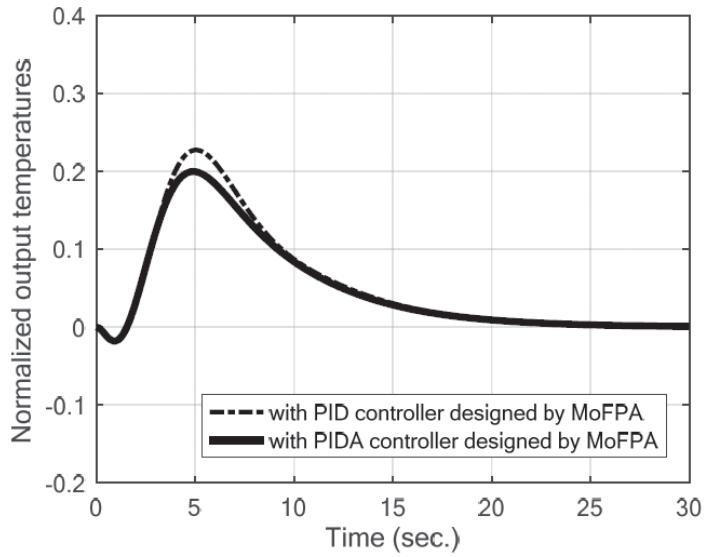


FIGURE 13. Load-regulating responses of the electric furnace temperature controlled system with PID and PIDA controllers optimized by MoFPA

From the input-tracking and load-regulating responses of the electric furnace temperature control system with the optimal PIDA controller designed by the MoFPA in Figure 12 and Figure 13, it can be noticed that the PIDA controller designed by the proposed MoFPA can provide very satisfactory response of the electric furnace temperature control system superior to the PID controller.

**5. Conclusions.** The application of the modified flower pollination algorithm (MoFPA) to optimal PIDA controller design for electric furnace temperature control system has been proposed in this paper. In the proposed MoFPA algorithm, the randomly switching probability has been employed for selection between local and global pollinations regarding to the flower pollination behavior in nature. The proposed MoFPA has been tested against five benchmark optimization problems compared with the original FPA to perform its performance. As results, the proposed MoFPA is more efficient and more robust in global optimum finding with higher success rates superior to the original FPA. The proposed MoFPA has been applied to optimal PIDA controller design for the electric furnace temperature control system considered as the constrained optimization problem based on modern optimization. As results of the control application, the PIDA controller has been optimized by the proposed MoFPA. The PIDA controller designed by the MoFPA could provide the very satisfactory input-tracking and load-regulating responses of the electric furnace temperature control system superior to the PID controller. For future research, applications of the proposed MoFPA will be extended to other real-world control engineering optimization problems including multi-objective, continuous and discrete optimization problems.

## REFERENCES

- [1] F. Glover and G. A. Kochenberger, *Handbook of Metaheuristics*, Kluwer Academic Publishers, 2003.
- [2] E. G. Talbi, *Metaheuristics from Design to Implementation*, John Wiley & Sons, 2009.
- [3] T. Ganesan, P. Vasant and I. Elamvazuthi, *Advances in Metaheuristics: Applications in Engineering Systems*, CSC Press, Taylor & Francis Group, 2017.
- [4] S. Dash, B. K. Tripathy and A. U. Rahman, *Handbook of Research on Modeling, Analysis, and Application of Nature-Inspired Metaheuristic Algorithms (Advances in Computational Intelligence and Robotics)*, IGI Global Engineering Science Reference, 2018.
- [5] D. E. Goldberg, *Genetic Algorithm in Search, Optimization, and Machine Learning*, Addison-Wesley Publishing, 1989.
- [6] K. V. Price, R. M. Storn and J. A. Lampinen, *Differential Evolution: A Practical Approach to Global Optimization*, Springer, 2006.
- [7] S. Kirkpatrick, C. D. Gelatt and M. P. Vecchi, Optimization by simulated annealing, *Science*, vol.220, pp.671-680, 1983.
- [8] O. K. Erol and I. A. Eksin, A new optimization method: Big bang-big crunch, *Advances in Engineering Software*, vol.37, pp.106-111, 2006.
- [9] J. Kennedy and R. Eberhart, Particle swarm optimization, *Proc. of the 1995 IEEE International Conference on Neural Networks*, pp.1942-1948, 1995.
- [10] M. Dorigo, M. Birattari and T. Stutzle, Ant colony optimization, *IEEE Transactions on Computer Intelligence*, vol.1, pp.28-39, 2006.
- [11] X. S. Yang, A new metaheuristic bat-inspired algorithm, *Studies in Computational Intelligence*, vol.284, pp.65-74, 2010.
- [12] X. S. Yang, Firefly algorithms for multimodal optimization, *Lecture Notes in Computer Science*, vol.5792, pp.169-178, 2009.
- [13] R. Oftadeh, M. J. Mahjoob and M. Shariatpanahi, A novel meta-heuristic optimization algorithm inspired by group hunting of animals: Hunting search, *Computers and Mathematics with Applications*, vol.60, pp.2087-2098, 2010.
- [14] S. Mirjalili, S. M. Mirjalili and A. Lewis, Grey wolf optimizer, *Advances in Engineering Software*, vol.69, pp.46-61, 2014.
- [15] S. Mirjalili and A. Lewis, The whale optimization algorithm, *Advances in Engineering Software*, vol.95, pp.51-67, 2016.
- [16] X. S. Yang and S. Deb, Cuckoo search via Lévy flights, *Proc. of the World Congress on Nature & Biologically Inspired Computing (NABIC 2009)*, pp.210-214, 2009.
- [17] X. S. Yang, Flower pollination algorithm for global optimization, *Unconventional Computation and Natural Computation, Lecture Notes in Computer Science*, vol.7445, pp.240-249, 2012.
- [18] G. G. Wang, S. Deb and Z. Cui, Monarch butterfly optimization, *Neural Computing and Applications*, pp.1-20, 2015.
- [19] F. Glover and M. Laguna, *Tabu Search*, Kluwer Academic Publishers, 1997.
- [20] Z. W. Geem, J. H. Kim and G. Loganathan, A new heuristic optimization algorithm: Harmony search, *Simulation*, vol.76, pp.60-68, 2001.
- [21] J. A. Rezaee, Brainstorm optimisation algorithm (BSOA): An efficient algorithm for finding optimal location and setting of FACTS devices in electric power systems, *International Journal of Electrical Power & Energy Systems*, vol.69, pp.48-57, 2015.
- [22] D. Puangdownreong, Spiritual search: A novel metaheuristic algorithm for control engineering optimization, *International Review of Automatic Control*, vol.11, no.2, pp.86-97, 2018.
- [23] X. S. He, X. S. Yang, M. Karamanoglu and Y. X. Zhao, Global convergence analysis of the flower pollination algorithm: A discrete-time Markov chain approach, *Procedia Computer Science*, vol.108, pp.1354-1364, 2017.
- [24] H. Chiroma, N. L. M. Shuib, S. A. Muaz, A. I. Abubakar, L. B. Ila and J. Z. Maitama, A review of the applications of bio-inspired flower pollination algorithm, *Procedia Computer Science*, vol.62, pp.435-441, 2015.
- [25] Z. A. A. Alyasseri, A. T. Khader, M. A. Al-Betar, M. A. Awadallah and X. S. Yang, Variants of the flower pollination algorithm: A review, nature-inspired algorithms and applied optimization, *Studies in Computational Intelligence*, vol.744, pp.91-118, 2018.
- [26] E. Nabil, A modified flower pollination algorithm for global optimization, *Expert Systems with Applications*, vol.57, pp.192-203, 2016.

- [27] D. Rodrigues, X. S. Yang, A. N. De Souza and J. P. Papa, Binary flower pollination algorithm and its application to feature selection, *Recent Advances in Swarm Intelligence and Evolutionary Computation*, pp.85-100, 2015.
- [28] M. Y. Shambour, A. A. Abusnaina and A. I. Alsalibi, Modified global flower pollination algorithm and its application for optimization problems, *Interdisciplinary Sciences: Computational Life Sciences*, pp.1-12, 2018.
- [29] B. J. Glover, *Understanding Flowers and Flowering: An Integrated Approach*, Oxford University Press, 2007.
- [30] P. Willmer, *Pollination and Floral Ecology*, Princeton University Press, 2011.
- [31] K. Balasubramani and K. Marcus, A study on flower pollination algorithm and its applications, *International Journal of Application or Innovation in Engineering and Management*, vol.3, pp.320-325, 2014.
- [32] I. Pavlyukevich, Lévy flights, non-local search and simulated annealing, *Journal of Computational Physics*, vol.226, pp.1830-1844, 2007.
- [33] M. M. Ali, C. Khompatraporn and Z. B. Zabinsky, A numerical evaluation of several stochastic algorithms on selected continuous global optimization test problems, *Journal of Global Optimization*, vol.31, pp.635-672, 2005.
- [34] M. Jamil and H.-J. Zepernick, Test functions for global optimization: A comprehensive survey, in *Swarm Intelligence and Bio-Inspired Computation: Theory and Applications*, X. S. Yang et al. (eds.), Elsevier Inc., 2013.
- [35] J. Paulusová and M. Dúbravská, Application of design of PID controller for continuous systems, *Humusoft.Cz*, (1), pp.2-7, 2012.
- [36] S. Jung and R. C. Dorf, Analytic PIDA controller design technique for a third order system, *Proc. of the 35th IEEE Conference on Decision and Control*, pp.2513-2518, 1996.
- [37] W. Budiharto, E. Irwansyah, J. S. Suroso and A. A. S. Gunawan, Design of object tracking for military robot using PID controller and computer vision, *ICIC Express Letters*, vol.14, no.3, pp.289-294, 2020.
- [38] C. Thammarat and D. Puangdownreong, CS-based optimal  $PI^{\lambda}D^{\mu}$  controller design for induction motor speed control system, *International Journal on Electrical Engineering and Informatics*, vol.11, no.4, pp.638-661, 2019.
- [39] T. Jitwang and D. Puangdownreong, Application of cuckoo search to robust PIDA controller design for liquid-level system, *International Journal of Innovative Computing, Information and Control*, vol.16, no.1, pp.189-205, 2020.
- [40] K. Lurang and D. Puangdownreong, Two-degree-of-freedom PIDA controllers design optimization for liquid-level system by using modified bat algorithm, *International Journal of Innovative Computing, Information and Control*, vol.16, no.2, pp.715-732, 2020.