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Research Article

Comparison of Optimization Methods for Temperature Control of a Heat Flow System

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Abstract

In this paper, the proportional-integral (PI) controller parameters have been determined by using various optimization methods for the heat flow system (HFS), which is a time-delayed system, and then the temperature control performance of the HFS has been evaluated under multiple time-varying reference inputs. First, a short mathematical model expression of the HFS has been derived. Secondly, the controller parameters have been tuned by using Genetic Algorithm (GA), Bee Colony Optimization (BCO), Ant Colony Optimization (ACO), Grey Wolf Optimization (GWO) and Cuckoo Search Optimization (CO). The performance of the PI controllers obtained via these optimization methods has been compared to those derived from the classical Ziegler-Nichols (Z-N) method. Simulation results have been evaluated in terms of reference temperature tracking accuracy, controller response to sudden changes in the reference signal, maximum overshoot, rise time, and settling time. To quantitatively assess the performance, the Mean Absolute Error (MAE) has also been calculated for each method and compared to that of the Z-N approach. The simulation results have indicated that the controller parameters obtained by using the GWO achieved superior reference temperature tracking performance compared to those obtained using the other optimization algorithms.

Keywords: Heat flow system, linear control, PI controller, optimization methods, optimization-based control.

Bir Isı Akış Sisteminin Sıcaklık Kontrolü için Optimizasyon Yöntemlerinin Karşılaştırılması

Öz

Bu çalışmada, zaman gecikmeli bir sistem olan Isı-Akış Sistemi (IAS) için lineer kontrolcü parametreleri K_p ve K_i değerleri çeşitli optimizasyon yöntemleri kullanılarak belirlenmiş ve sistemin sıcaklık kontrol performansı zamanla değişen referans sıcaklıklar altında test edilmiştir. İlk olarak IAS'nin matematiksel modeli elde edilmiştir. İkinci olarak; kontrolcü parametreleri sırasıyla Genetik Algoritma (GA), Arı Koloni Optimizasyonu (AKO), Karınca Koloni Optimizasyonu (KKO), Gri Kurt Optimizasyonu (GKO) ve Guguk Kuşu Optimizasyonu (GKO) yöntemleri ile optimize edilmiştir. Ayrıca bu yöntemlerle elde edilen $K_p$ve K_i değerleri, klasik Ziegler-Nichols (Z-N) yöntemi ile bulunan parametrelerle kıyaslanmıştır. Simülasyonlar sonucunda, her bir yöntemin referans sıcaklık takip başarımı, ani referans değişimlerine karşı gösterdiği kontrolcü tepkisi, maksimum aşım, yükselme süresi ve yerleşme süresi gibi performans ölçütleri açısından değerlendirilmiştir. Bununla birlikte, her optimizasyon yöntemi için Ortalama Mutlak Hata (OMH) değeri hesaplanarak referans takip hatası sayısal olarak ortaya konmuştur. Elde edilen bulgular, GKO ile elde edilen kontrolcü parametrelerinin diğer yöntemlere kıyasla daha düşük hata ile referans sıcaklık takibi sağladığını göstermektedir.

Anahtar Kelimeler: Isı-akış sistemi, lineer kontrol, optimizasyon metotları, optimizasyon tabanlı kontrol.

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1. Introduction

Temperature control has taken its place in many areas of our lives and its importance has started to increase day by day. There are areas of use in industry, ambient temperature measurement, and devices. In practise, there are control applications such as temperature set point, temperature uniformity, temperature profile monitoring.

Numerous studies in the literature focus on temperature control in various systems. Vesovic and Jovanovic [1], for instance, have proposed a hybrid approach combining fuzzy logic and neural networks to model heat transfer phenomena. Recognizing the limitations of linear models in accurately capturing the system's dynamics, they have employed a genetic algorithm to train an ANFIS structure. Their findings have demonstrated that the nonlinear identification using ANFIS method closely matched the behaviour of the actual system with minimal error. Moreover, the ANFIS-based model has exhibited enhanced performance over traditional identification methods, particularly in adapting to dynamic system changes and managing noisy input data effectively. Al-Saggaf et al. [2] have proposed a novel fractional-order linear active disturbance rejection control (FO-LADRC) strategy, formulated as a model-free analytical design methodology. The effectiveness of the approach, particularly in terms of enhanced robustness and precise trajectory tracking, was experimentally validated using a heat flux system. Given the system's inherent time-delay characteristics, a series of tests were performed to assess the controller's performance under various conditions. The findings consistently indicated that the FO-LADRC outperforms its integer-order counterpart, delivering superior tracking accuracy and improved disturbance rejection capabilities. Jovanovic and Zaric [3] have first experimentally obtained the mathematical model of the heat flow system. Then, in order to examine the nonlinear behaviour of the system, a Takagi-Sugeno (TS) fuzzy model was created based on three linear models. Although this model provides superiority in capturing nonlinearities, it was observed that the model optimized the unknown parameters in the rule premises with the GWO method. Then, fuzzy controllers based on both the initial and optimized TS model were developed using the Parallel Distributed Compensation (PDC) method. It was observed that the TS models developed with GWO increased the efficiency of the PDC-based controller. Ionesi and Jouffroy [4] have presented a second-order model representing the heat flow in the air handling unit found in compact HVAC systems. They have discussed a heat flow experiment conducted by Quanser, whose thermodynamics are very close to those of an AHU, and showed a good match between the measured and targeted parameters and conditions. As a result, a good convergence of the parameters was observed using the parameters estimated by standard estimation methods as a baseline. Malek et al. [5] have studied the FOC design for a class of FO-systems, using the fractional pole time delay system model as a starting point. It is observed that the derived model can able to drive the HFE system to step reference better than the integer order system. Also, the results of simulation and experimental results have been examined that the designed two FO-controllers showed better performance compared to the integer-order controller used in the simulation and experimental studies. Nath et al. [6] have proposed an IMC-PID control method designed with a fuzzy-tuning rule. The value of the IMC tuning parameter (such as the closed-loop time constant k) has been changed online by a rule-based table consists of twenty-five rules. The experimental results realized on the level and temperature control systems have clearly proved the superiority of the designed fuzzy rule-based method. Matijevic et al. [7] have tested an existing concept, detailing the technical requirements, definition, implementation and validation of a process trainer. In addition, they have presented three possible training tasks with a software infrastructure developed for remote control of a laboratory setup via the Internet. They have demonstrated the usability of the model in applied engineering training using a PID controller whose parameters were set to the Dahlin algorithm and the Z-N tuning. As a result, they have observed to achieve different training tasks. Ahn et al. [8] have proposed a fractional integral derivative controller (FIDC) via a new analytical tuning method so as to applied to the HFE system. The performance of the proposed FIDC has been compared with the integer-order PI/PID controller and the FO-PI controller. When the experimental results have been checked, as well as comparison with the conventional PI/PID controller based on the Z-N method, it is shown that the designed controllers have particularly useful in terms of controlling the HFS also known as time-delayed heat flux systems. Yılmaz et al. [9] have realized a real-time optimization-based liquid level control of a coupled tank system for two different configurations. To realize liquid level control, they have obtained K_{ff} (feed-forward controller parameter), K_p and K_i parameters via Z-N and GA optimization methods. The experimental results have showed that the controller parameter results obtained based on GA method, have performed the liquid level control more successfully compared to the other methods.

In this paper, the linear controller parameters of the HFS have been obtained by various optimization methods such as GWO, GA, BCO, CO, ACO and Z-N as well. The obtained parameters have then tested under step + sinusoidal, square and sawtooth reference temperatures signals. When the obtained results have been examined, it has been observed that the temperature tracking performed with the controller parameters obtained with the GWO method, is more successful than the other methods. In addition, it is observed that the results obtained with the GA, ACO, BCO, CO methods used in the simulation studies, have performed more successful temperature tracking than ZN method approximately at least 11%.

2. Material and Methods

In this section, the mathematical model of HFS and all optimization methods used in this study have been presented.

2.1. The Heat Flow System

The Quanser Heat Flow System (HFE) includes specific optimization models and experiments. Using a heater and a fan, the air temperature is measured from three temperature sensors at selected points on a duct and a model is obtained from the response of the system, and a *PI* controller is designed to control the system. By applying an analogue step signal to the HFS, the temperature changes at each sensor can be observed.

The following formula can be used for the thermodynamic model of system [10]-[12]:

$$\frac{d}{dt}Tn = F(Vh, Vb, Ta, Xn) \tag{1}$$

where T_n is the temperature at the nth sensor, V_h is the voltage applied to the heater, V_b is the voltage applied to the fan, T_a is the ambient temperature and X_n is the distance of the nth sensor to the heater [10]. The operating curves of the system must be obtained from the measurements from each sensor. The first-order model of the system to be derived in this way should be approximately written as follows [10], [11]:

$$T_n(s) = \frac{K_n V_h(s)}{T_n s + 1} \tag{2}$$

where T_n and K_n represent the time constant and steady state gain for the nth sensor [10].

Another issue is temperature control. The temperature of the room is maintained using an on-off control and a compensator. The voltage-temperature transfer function of the HFS can be written as given below [10].

$$G(s) = \frac{T(s)}{V(s)} = \frac{K}{Ts + 1} \tag{3}$$

The PI controller equation for a feedback control system that will control the temperature at the first sensor of the system and reset the steady-state error is as follows [10], [11].

$$V_q = K_p(T_{1d} - T_1) + \frac{K_i}{s}(T_{1d} - T_1) \tag{4}$$

If this expression is used in a closed loop system, the following relation is obtained as given below [10], [11].

$$\frac{T_1}{T_{1d}} = \frac{G\left(K_p s + K_i\right)}{s^2 T + \left(K_p G + 1\right)s + G K_i} \tag{5}$$

2.2. Optimization Methods

There are some methods used to find the control parameters of a heat flow system. Some of them are genetic algorithm optimization method, bee colony optimization method, ant colony optimization method, grey wolf optimization method, cuckoo optimization method and Z-N optimization method.

A. Genetic Algorithm Optimization Method

GA is a population-based search algorithm inspired by the principles of natural selection and genetics. It is widely used to find efficient solutions to complex and nonlinear optimization problems. GA works on a population of possible solutions and uses genetic operators to improve this population according to a specified fitness function. The GA starts with a randomly generated initial population of individuals. A fitness function is a function that evaluates how "good" each individual is with respect to the optimization goal.

In controller optimization of heat flow systems, the fitness function is usually based on the frequency domain or time domain performance characteristics of the system. The aim is to find best controller parameters that maximize or minimize the value of the fitness function. The selection operator determines which individuals in the current population will be selected to pass on their genes to the next generation [13]. Individuals with higher fitness are more likely to be selected. This mimics the principle of "survival of the fittest." The crossover operator creates new offspring from two selected parent individuals. The goal is to obtain better solutions by combining the good features of the parents. The mutation operator makes small random changes to the newly created offspring. The goal is to prevent the population from getting stuck in local optima and to allow for a wider exploration of the search space. After applying the selection, crossover and mutation operators, a new population of individuals is created. This new population contains new solution candidates that will be evaluated in the next iteration. GA continues iteratively until a certain termination criterion is met. Moreover, the population size is taken as 50, the mutation rate is taken as 0.2, the number of generations is taken as 120, respectively [14].

The output equation of a PI controller is [15]:

$$u(t) = Kp.e(t) + Ki\int_0^t e(\tau)d\tau \tag{6}$$

$$J(Kp, Ki) = \int_0^T [e(t)^2]dt \tag{7}$$

Since the genetic algorithm seeks to find the minimum, the fitness function is usually defined as:

$$Fitness(x) = \frac{1}{J(x) + \varepsilon} \tag{8}$$

The following formulation can be directly applied to optimize the PI controller gains of a heat flux system.

$$J(x) = \int_0^\tau e^2(t; x)dt \tag{9}$$

B. Grey Wolf Optimization Method

The GWO method is inspired by the hunting behaviour and social hierarchy of grey wolves [16]. In the optimization algorithm, each solution in the initial population represents a wolf. The fitness function determines "how successful a hunter" each wolf is. N number of grey wolves are randomly created within the specified boundaries. Each worm is a vector representing the controller parameters. For each worm in the initial population, the performance of the heat flux system is simulated or tested on the real system using the relevant controller parameters. The best three wolves are determined according to their suitability values (alpha (α), beta (β) and delta (δ)). When the stopping criterion is satisfied, the position of the alpha wolf with the best fitness value represents the optimized controller parameters for the heat flow system [17]. For this study, the number of wolves is taken as 25.

It is aimed to optimize the controller parameters of a controller such as a PI controller [18]:

$$J(x) = \int_0^{\tau} e^2(t;x)dt \tag{10}$$

Calculating the distance of the prey is given below [18].

$$\vec{D} = \left|\vec{C}.\vec{X}leader - \vec{X}\right| \tag{11}$$

Here $\vec{C} = 2\vec{r}_2$ represents the control vector and $\vec{r}_2 : [0,1]$ random vector as well. Location update rule:

$$\vec{X}(t+1) = \vec{X}leader - \vec{A}.\vec{D} \tag{12}$$

where $\vec{A} = 2\vec{r}_1$ represents a control vector and $\vec{r}_1 : [0,1]$ represents a random vector as well. Each individual updates her position based on the influence of 3 leaders:

$$\vec{X}(t+1) = \frac{1}{3}\left(\overrightarrow{X1} + \overrightarrow{X2} + \overrightarrow{X3}\right) \tag{13}$$

To measure the controller performance in the HFS, a performance criterion such as the following is used in (14) [18].

$$Fitness(x) = \frac{1}{J(x) + \varepsilon} \tag{14}$$

C. Ant Colony Optimization Method

The ACO is a meta-heuristic optimization algorithm inspired by the shortest path finding behaviour of ants in nature. Ants follow random paths to find a food source, but when they find one, they leave pheromones along the path. Over time, shorter paths become marked with more pheromones, and other ants begin to prefer those paths as well.

Each ant produces a solution. Then, pheromone is released on the path according to the quality of this solution [19], [20]:

$$T_{ij}(t+1) = (1-\rho)T_{ij}(t) + \sum_{g=1}^{r} \Delta T_{ij}^{g}(t) \tag{15}$$

where T_{ij} is the pheromone density on the edge (*i*,*j*), $\rho = 0.15$ is the evaporation coefficient $(0 < \rho < 1)$ and $\Delta T_{ij}^{g}(t)$ is the contribution of ant *k* as well. The probability that an ant chooses the next parameter value in the solution space is [19]-[21]:

$$P_{ij}^{k}(t) = \frac{[Tij(t)]^{\alpha}.[\eta ij(t)]^{\beta}}{\sum l\epsilon Ni[Til(t)]^{\alpha}.[\eta il(t)]^{\beta}} \tag{16}$$

where the parameter $\alpha = 1$ controls the influence of the pheromone, $\beta = 2$ is the parameter that determines the influence of the heuristic information, N_i is the set of candidate neighbours which ant k can visit from the node i., and ηil is the heuristic information. Each ant tries a combination, the system is simulated with this combination and an error measure is calculated:

$$u(t) = K_p e(t) + K_i \int e(t)dt \tag{17}$$

D. Bee Colony Optimization Method

The BCO method is a meta-heuristic optimization algorithm inspired by the nectar collection behaviour of bees in nature. This algorithm is effectively used to optimize controller parameters in dynamic systems such as heat transfer systems. Bees signal the location of food sources to other bees by dancing. Bees near a productive source dance more, which encourages the colony to move toward that source. Also, for this study, the population size is taken as 40, the scout bee limit taken as 10, respectively.

For each solution, the initial parameters are chosen randomly [22]:

$$xij = xj^{min} + rand(0,1).\left(xj^{max} - xj^{min}\right) \tag{18}$$

The new solution vij is generated from the difference between the current solution and another random solution:

$$vij = xij + \phi ij.(xij - xkj) \tag{19}$$

where $k \neq i$ is another solution, xij is the current solution, and $\phi ij \in [-1,1]$ is a uniformly distributed random number as well. The probability of each solution being selected is calculated according to the fitness function as given below [23].

$$Pi = \frac{fiti}{\sum_{j=1}^{N} fitj} \tag{20}$$

The goal is to minimize the error function by optimizing the values:

$$u(t) = K_p e(t) + K_i \int e(t)dt \tag{21}$$

E. Cuckoo Optimization Method

The CO is based on the behaviour of some cuckoos in nature, which lay eggs in the nests of other birds [23]. Each cuckoo lays a single egg in a random nest. The best eggs are passed on to the next generation. If the nest owner discovers fake eggs, he or she may discard them or abandon the nest. This corresponds to a random change of solution. The solution space can be thought of as a "slot" for searching. Each "slot" represents a solution. These solutions are randomly initialized as given below [24]:

$$xi = xmin + rand(0,1).(xmax - xmin) \tag{22}$$

When creating a new solution, a small change is made to the existing solution. This change is modelled by Levy flight as given below [24].

$$xi^{new} = xi + \alpha.Levy(u) \tag{23}$$

where $\alpha > 0$ is the step size coefficient and taken as 0.25, and $Levy(u)$ is the random step drawn from Levy distribution. The fitness of each solution is calculated. In a heat flow system this usually means minimizing the error functions for the PI controller. That is, the fitness function can be written as given below [24].

$$fitness(xi) = \frac{1}{1 + J(xi)} \tag{24}$$

In the context of the heat flux system, PI control parameters are optimized according to:

$$u(t) = K_p e(t) \ + \ K_i \int e(t)dt \tag{25}$$

3. Results and Discussion

In this section, the simulation results are given for three different temperature references. In Fig. (2), the simulation results of all optimization methods under step + sinusoidal reference signal are given. As can be seen from the figure, the Z-N method has a higher rise time than the other optimization methods and also has a higher overshoot magnitude when compared with the other methods. On the other hand, although the other optimization methods have almost the same rise time, the GWO has settled to the reference temperature in a shorter time compared with the other methods. Moreover, the ACO and GA methods have the second and third best performances in terms of reference settling, respectively. On the other hand, for the time-varying part of the reference signal, due to sinusoidal signal form has smooth change with respect to time, all methods have similar reference tracking performance.

In Fig. (3), the error signals of all optimization methods under step + sinusoidal reference signal have been presented. First of all; when the step part of the reference signal is examined, the error value is the largest since the Z-N method has the highest overshoot value. On the other hand, although the other optimization methods have almost the same rise time, it is observed that the GWO approaches zero error value in a shorter time compared with the other methods. Second, when the time-varying part of the reference signal is applied, it is observed that the Z-N method has the largest error value. In addition, it has been observed that the GWO method has compensated the reference tracking error in a shorter time in the time-varying part of the reference as well as in the fixed part.

In Fig. (4), the control signals of all optimization methods for step + sinusoidal reference signal have been given. From the figure, it is seen that the Z-N method responds with a delay compared to the other optimization methods due to having the highest rise time. Moreover, although the other optimization methods have almost the same rise time, it is observed that the GWO, which settling the reference temperature signal earliest, have produced a control signal with a constant amplitude of 5 volts from about 1 to 28 seconds. Also, it has been observed that BCO and GA methods have produced a control signal with slight chattering. On the other hand, it has been observed that all methods have produced a control signal with a similar amplitude in the part of the reference that changes over time.

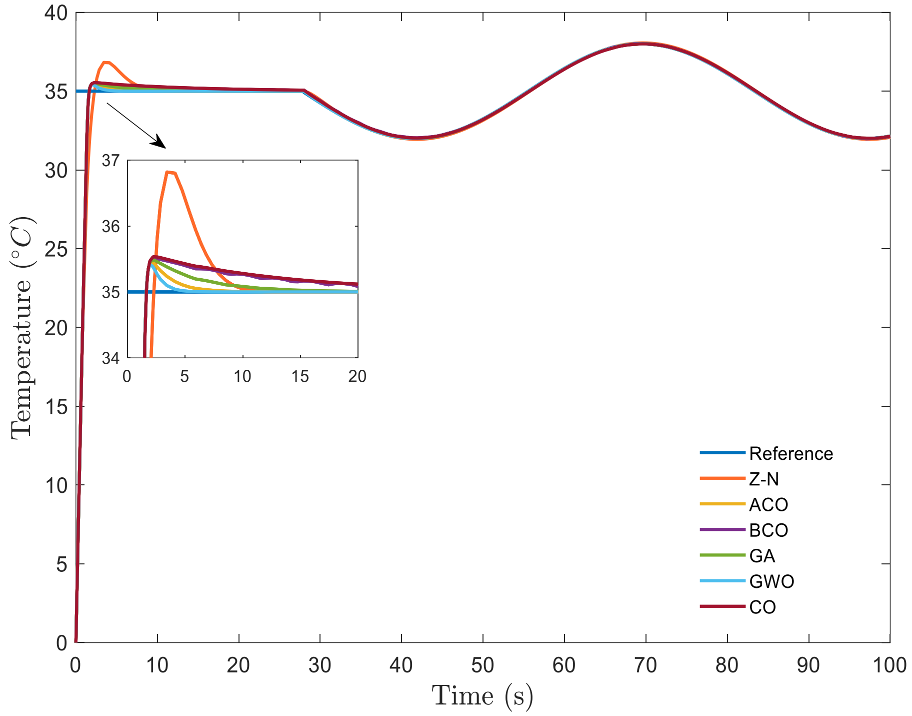

Figure 2. Simulation results of all optimization methods under step + sinusoidal reference signal.

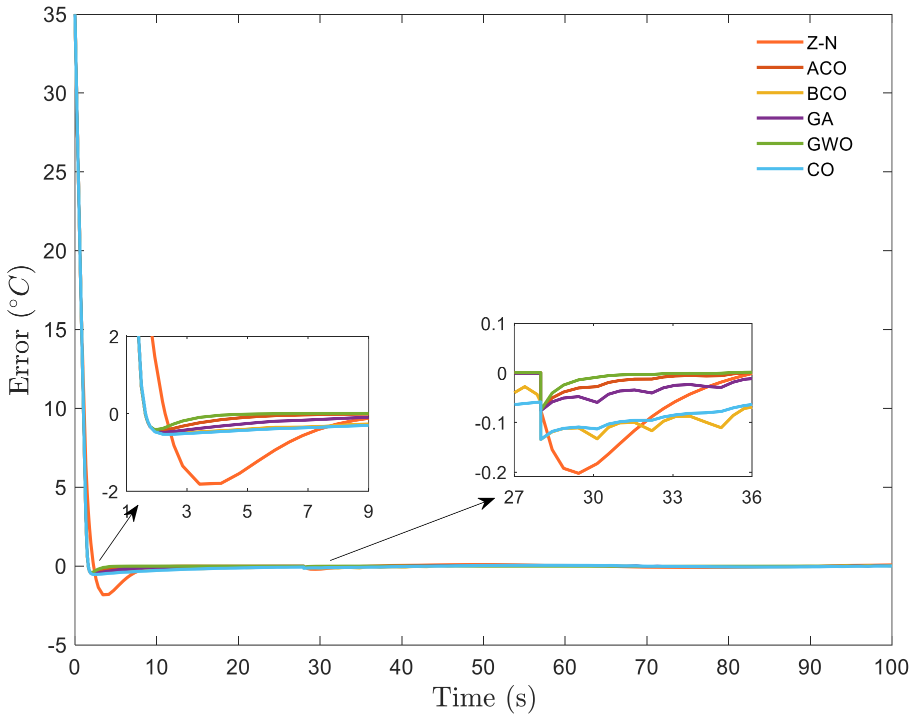

Figure 3. Error signals of all optimization methods under step + sinusoidal reference signal.

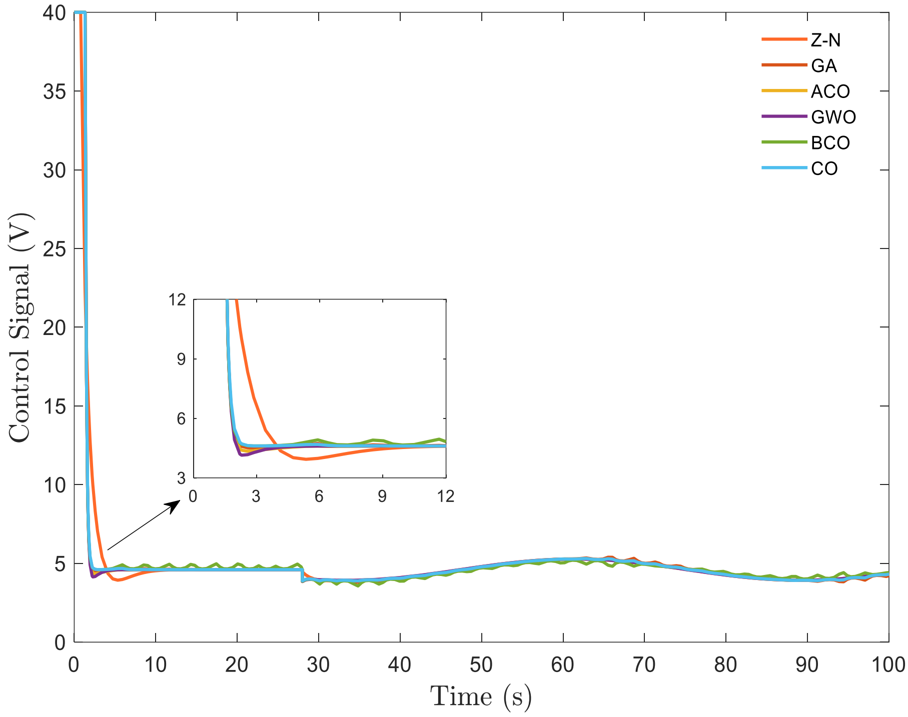

Figure 4. Control signals of all optimization methods for step + sinusoidal reference signal.

In table (1), the MAE values of all optimization methods under step + sinusoidal reference signal have been given. For step part of the reference signal, it is observed that the GWO, GA, ACO and BCO methods have approximately the same MAE value. Also, although CO method has higher MAE value than GWO, GA, ACO and BCO methods, it has lower MAE value than Z-N method. Moreover, although it is not clear from the reference temperature tracking, it is observed that GWO has the minimum MAE value in the sinusoidal part of the reference compared to other methods. On the other hand, when analysing the total improvement percentages, it is seen that the best improvement has been provided by GWO with a rate of approximately 13.18%. In addition, it is observed that the ACO has provided improvement 12.99%, GA 12.54%, BCO 11.58% and 11.36%, respectively compared to Z-N method.

Table 1. MAE values of all optimization methods under step + sinusoidal reference signal

Methods	STEP	SINUSOIDAL	STEP+SINUSOIDAL	TOTAL IMPROVEMENT % (wrt. Z-N)
GA	19.9978	0.0445	3.5680	%12.5468
ACO	19.9978	0.0262	3.5496	%12.9978
CO	20.0036	0.0921	3.6164	%11.3605
BCO	19.9978	0.0838	3.6072	%11.5860
GWO	19.9978	0.0184	3.5418	%13.1890
Z-N	21.2129	0.3590	4.0799	--------

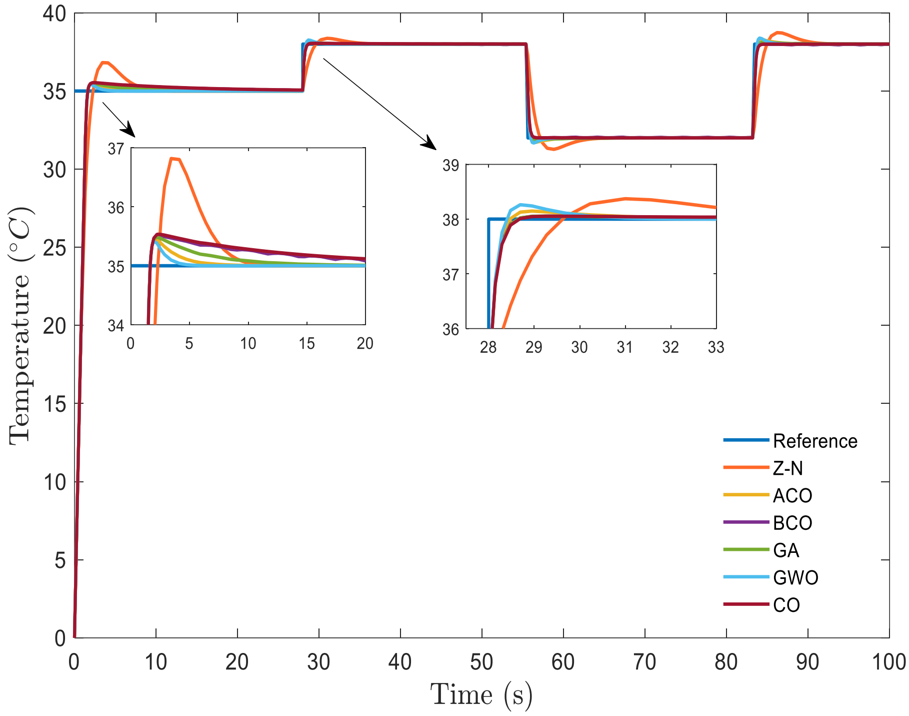

Figure 5. Simulation results of all optimization methods under step + square reference signal.

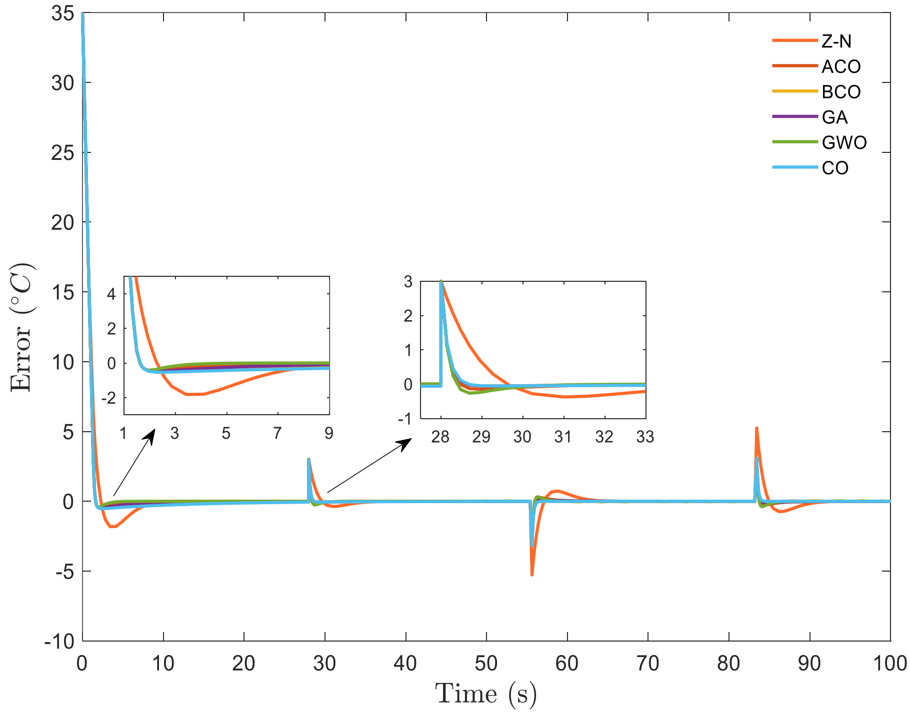

Figure 6. Error signals of all optimization methods under step + square reference signal.

When the Fig. (5) and Fig. (6) are both examined, according to the findings, GWO and ACO algorithms have the most successful methods to track the reference temperature value. The controller parameters obtained with these methods, have ensured that the system converged to the reference quickly and provided a stable response with minimum overshoot and minimum settling time. In addition, error graphs have revealed that these two methods have converged the tracking error to zero in a short time and did not contain oscillations in the transient regime. The GA, BCO and CA algorithms have also performed better than the Ziegler-Nichols (Z-N) method, but could not track as fast and with low errors as GWO and ACO. On the other hand, the traditional Z-N method has exhibited the lowest performance with significant overshoot, long settling time and high tracking errors.

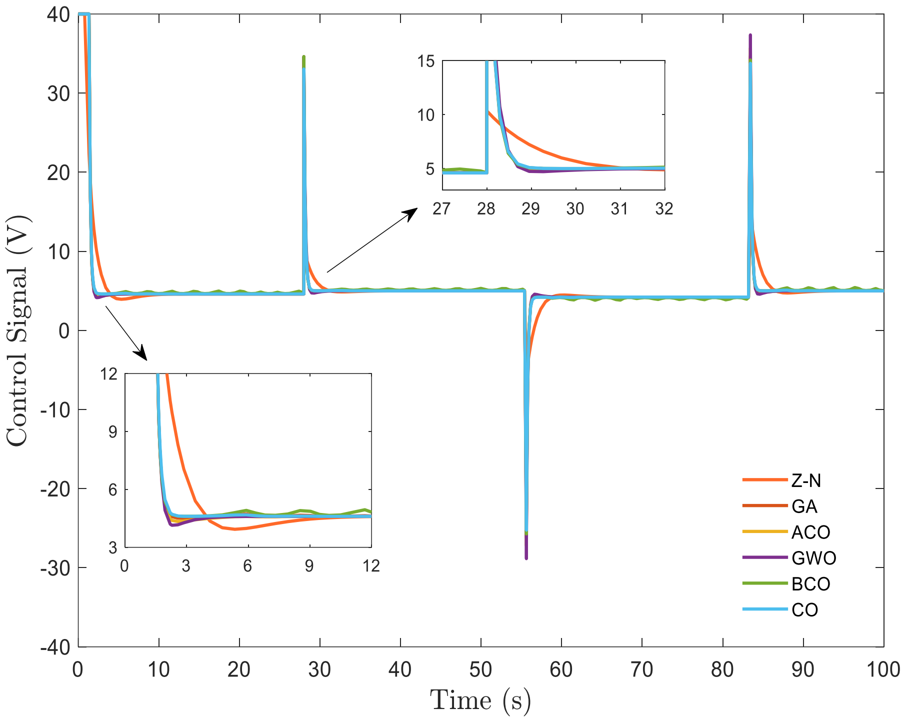

Figure 7. Control signals of all optimization methods for step + square reference signal.

In Fig. (7), the control signals of all optimization methods for step + square reference signal have been given. First, although the Z-N method has produced very high amplitude control signals (up to ±35V) as the other methods especially in sudden reference changes, it has less able to compensate for reference tracking errors. On the other hand, the GWO, CO, ACO, GA and BCO have produced approximately the same amplitude and stable control signals, which provided smoother and more efficient reference temperature tracking of the system.

Table 2. MAE values of all optimization methods under step + square reference signal

Methods	STEP	SQUARE	STEP+SQUARE	TOTAL IMPROVEMENT % (wrt. Z-N)
GA	19.9978	0.1581	3.6815	%17.7024
ACO	19.9978	0.1463	3.6697	%17.9662
CO	20.0036	0.1974	3.7217	%16.8037
BCO	19.9978	0.1890	3.7124	%17.0116
GWO	19.9978	0.1326	3.6560	%18.4348
Z-N	21.2129	0.7526	4.4734	----

In Table (2), the MAE values of all optimization methods are given under the step + square reference signal. For the step part; GA, ACO, BCO and GWO have had the same MAE values, which shows that all the mentioned optimization algorithm methods achieved the same performance. On the other hand, although the CO method has had a MAE value of approximately 20%, it has been observed that it still has a lower MAE value than the Z-N method. In the square form, which is the time-varying part of the reference, it has been seen that the method with the least MAE value has GWO, followed by ACO, GA, BCO and CO methods, respectively. As a result, as can be seen from the table, it has been observed that the method that showed the best reference temperature tracking performance compared to the Z-N method is GWO with an improvement rate of approximately 18.43%.

In Fig. (8), the simulation results of all optimizations methods have been presented under step + sawtooth reference signal. The sawtooth reference includes a sudden change and then a smooth change. The sawtooth reference first contains sudden and then smooth changes. Therefore, it is one of the common methods used to observe the performance of optimization methods. First of all, when the figure is examined between 0-5 seconds, it has seen that all optimization methods except the Z-N method have reached the reference signal in around 2.5 seconds. Then, it has been observed that the GWO method has caught the reference signal in a short time and ACO, GA methods have caught the reference, respectively. Moreover, although the CO and BCO methods have both settled on the reference signal in a longer time than the Z-N method, it has been observed that the ZN method has significantly bigger overshoot magnitude value, thus performing worse reference temperature tracking than the other optimization methods.

In Fig. (9), the error signals of all optimization methods have been depicted for step + sawtooth reference signal. For the step part of the reference signal; it has been observed that the parameter values obtained with the GWO method have reached zero error value at the earliest, followed by the ACO, GA, CO and BCO methods, respectively. In the time-varying part of the reference signal, it has been observed that the method that responded fastest to sudden changes and resets the error is GWO, followed by ACO, GA, CO and BCO methods, respectively.

In Fig. (10), the control signals of all optimization methods have been presented. When the control signal amplitudes that produced for the step part of the reference signal have been examined, it has been observed that all methods have produced approximately 40 volts control signal magnitude to reach the reference temperature signal, and then produced a control signal around 5 volts when they have settled the reference signal. When the sawtooth signal reference signal has been applied, it is observed that the Z-N method have produced the lowest amplitude control signal around between 5-15 volts. On the other hand, it is observed that all optimization methods have produced higher amplitude control signals around between 5-38 volts depending on the parameter optimizations. Thus, it has been observed that all optimization methods have increased their reference temperature tracking performance by producing higher amplitude control signals.

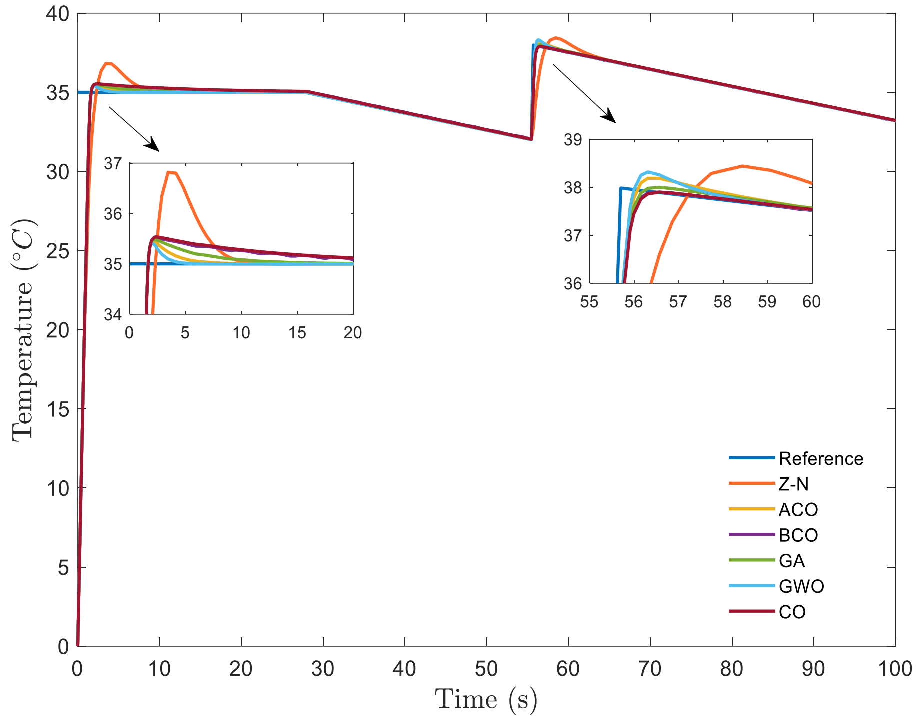

Figure 8. Simulation results of all optimization methods under step + sawtooth reference signal.

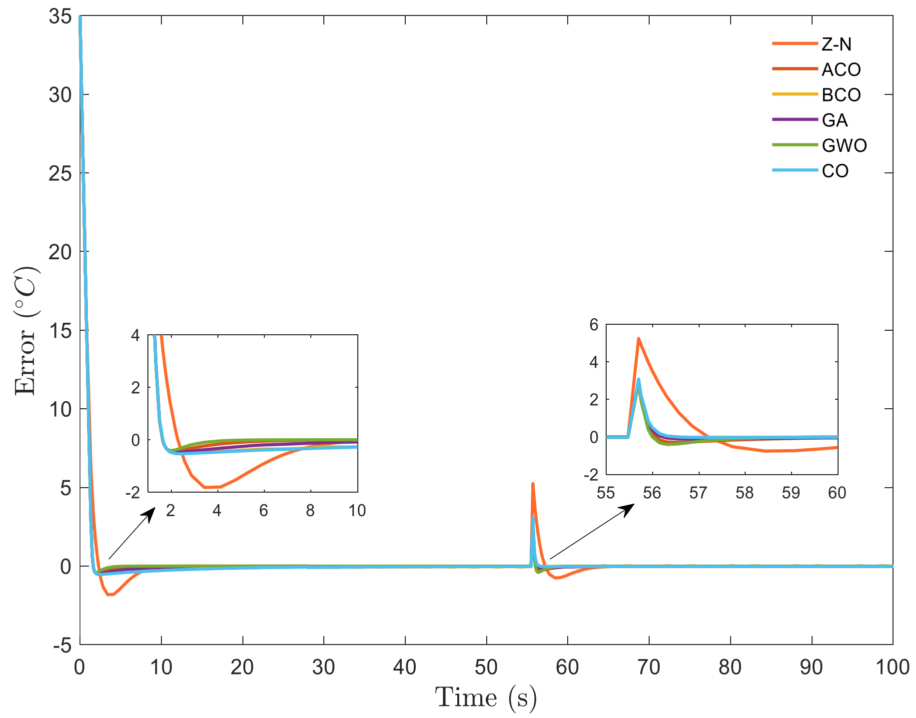

Figure 9. Error signals of all optimization methods under step + sawtooth reference signal.

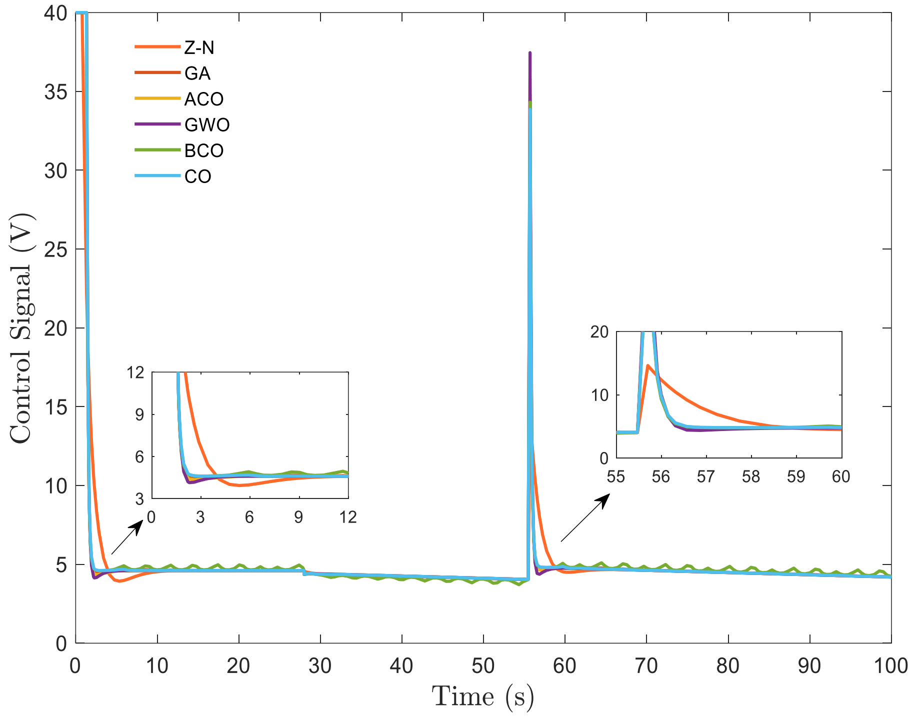

Figure 10. Control signals of all optimization methods for step + sawtooth reference signal.

In Table (3), the MAE values of all optimization methods are given under the step + sawtooth reference signal. For the step part; GA, ACO, BCO and GWO have had the same MAE values around 19.99 %, which shows that all the mentioned optimization methods achieved the same performance in terms of rise time, settling time and overshoot magnitude values. Moreover, although the CO method has a slightly higher MAE value compared to the other optimization methods, it has been still seen to have a lower MAE value with respect to the Z-N method. For the sawtooth reference has been applied, it has been observed that the method with the lowest MAE value is GWO, followed by ACO, GA, BCO and CO methods, respectively. As a result, it has been observed from the table that the method providing the best reference temperature tracking performance compared to the Z-N method is performed with the controller parameters obtained with GWO, followed by the controller parameters obtained with the ACO, GA, BCO and CO methods, respectively.

Table 3. MAE values of all optimization methods under step + sawtooth reference signal

Methods	STEP	SAWTOOTH	STEP + SAWTOOTH	TOTAL IMPROVEMENT % (wrt. Z-N)
GA	19.9978	0.0853	3.6088	%15.0250
ACO	19.9978	0.0692	3.5927	%15.4041
CO	20.0036	0.1312	3.6555	%13.9254
BCO	19.9978	0.1241	3.6475	%14.1138
GWO	19.9978	0.0581	3.5815	%15.6678
Z-N	21.2129	0.5261	4.2469	--------

Conclusion

In this paper, the linear controller parameters of the HFS have been obtained by using various optimization methods such as ACO, CO, BCO, GA and GWO. Then, the performances of the obtained controller parameters have been tested under step + time varying references. Also, the performances of the results of all the mentioned methods are compared with the result of Z-N method. The findings are as follows

- For step + sinusoidal reference temperature signal results have been examined; it is observed that the best improvement is achieved with the parameters obtained via the GWO method with a rate of approximately 13.18% wrt. Z-N method. Besides, when the reference temperature tracking performances of the controller parameters obtained with other methods have been analysed; the improvement rates compared to Z-N are observed as ACO, GA, BCO and CO methods, respectively.
- As a second simulation study; when the step + square reference temperature signal was applied, the analysis indicates that the GWO-based parameters provide the highest improvement, approximately 18.43% over Z-N. The performance improvements of the remaining methods compared to Z-N follow the order: ACO, GA, BCO, and CO.
- For the last study realised via step + sawtooth reference temperature signal; the examination of the results reveals that the GWO method again yields the best improvement, around 15.66% relative to Z-N. The improvement rates of the other methods with respect to Z-N are observed in the same order: ACO, GA, BCO, and CO.

In conclusion; this study aims to improve the reference temperature tracking performance of the HFS by obtaining the PI controller parameter values with various optimization methods. When the simulation results have been examined; it is observed that the simulation results performed with the controller parameters determined with the GWO method, perform better reference temperature tracking compared to the results obtained with other optimization methods. In addition, it is seen that the simulation results obtained as a result of the K_p and K_i controller parameters obtained with the GA, ACO, BCO, CO used in the simulation studies perform more successful reference temperature tracking compared to the traditional Z-N method.

Ethics in Publishing

There are no ethical issues regarding the publication of this study.

Author Contributions

Ferhan Karadabağ: Designing the study, collecting the data, evaluating the results, writing the article, Kaan Can: Collecting the data, evaluating the results, writing the article.

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