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MEMETIC ALLIGATOR OPTIMIZATION ALGORITHM FOR OPTIMAL THERMOREGULATORY CONTROL IN PIPING SYSTEMS

WENG-HOOI TAN, NORAMALINA ABDULLAH*, JUNITA MOHAMAD-SALEH

*School of Electrical & Electronic Engineering, Universiti Sains Malaysia,
Nibong Tebal, 14300, Penang, Malaysia*

**Corresponding author: eenora@usm.my*

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ABSTRACT: Applying optimization techniques to control systems remains a challenging task. Control system technology is emerging rapidly due to the high demands for commercialization in engineering and industrial fields, but existing optimization techniques are considered weak to cope with increasingly complex control problems. More powerful optimization techniques are urgently needed to catch up with the prerequisites for optimal control. Hence, this research is dedicated to the development of an improved optimization algorithm to solve the optimal thermoregulatory control problem for piping systems in a more efficient manner. As a research outcome, the Memetic Alligator Optimization (MeAgtrO) algorithm is proposed. On top of the mathematical hunting and relocating mechanisms, MeAgtrO adds several evolutionary operators that replicate satiety awareness, mating, generational alternation, and dispersed hunting. Unlike the standard optimizer, which only emphasizes global and local search transitions, these improved variants give the ability to shuffle, swap, replace, and disperse agent information for greater flexibility. Upon application to a simulated piping system to optimally control thermoregulation processes, MeAgtrO statistically outperformed the other compared algorithms, showing 100% accuracy, 99.99% precision, and 99.99% robustness in minimizing the tracking error, response time, and equipment burden of the system. MeAgtrO has been shown to have high processing speed for optimal application control, which corresponds to its superior convergence speed to stabilize at 40% of iterations. While showing satisfactory clustering properties, MeAgtrO also demonstrated the best step response with a rise time of 0.40s, settling time of 0.99s, 0 tracking error, 0% overshoot, and 0% undershoot.

ABSTRAK: Penerapan teknik optimasi pada sistem kawalan adalah tugas mencabar. Teknologi sistem kawalan berkembang pesat disebabkan oleh permintaan tinggi bagi komersialisasi dalam bidang kejuruteraan dan industri, tetapi teknik optimasi sedia ada dianggap lemah dalam mengatasi masalah kawalan yang semakin kompleks. Teknik optimasi lebih kuat diperlukan dengan segera untuk memenuhi prasyarat kawalan optimal. Oleh itu, penyelidikan ini bertujuan bagi membangunkan algoritma optimasi yang lebih baik bagi menyelesaikan masalah kawalan termoregulator optimum pada sistem paip dengan lebih cekap. Penyelidikan ini mencadangkan algoritma Memetic Alligator Optimization (MeAgtrO). Selain dari mekanisme pemindahan dan pemburuan matematik, MeAgtrO memiliki beberapa pengendali evolusinari yang menggandakan kesedaran kenyang, mengawan, alternasi generasi, dan pemburuan tersebar. Berbeza dengan pengoptimuman standard, penekanan hanya pada peralihan global dan carian tempatan, ini membaiki varian dengan memberikan keupayaan menyusun semula, menukar, mengganti, dan menyebar maklumat ejen bagi fleksibiliti yang lebih besar. Apabila digunakan pada sistem paip bersimulasi bagi mengawal proses termoregulasi secara optimum, MeAgtrO secara statistik mengatasi algoritma lain, menunjukkan ketepatan 100%, kejituan 99.99%, dan kekuatan 99.99% dalam mengurangkan kesilapan pengesanan, masa tindak balas, dan beban sistem peralatan. MeAgtrO telah terbukti mempunyai kelajuan pemprosesan yang tinggi bagi aplikasi kawalan optimum, sejajar dengan kelajuan konvergensi yang lebih bagus bagi menstabilkan iterasi 40%. Di samping menunjukkan sifat kelompok yang memuaskan, MeAgtrO juga memiliki respons langkah terbaik kenaikan masa 0.40s, masa penyelesaian 0.99s, ralat pengesanan 0%, lebih sasaran 0%, dan kurang sasaran 0%.

KEYWORDS: *bio-inspired, metaheuristic, optimization, thermoregulation in piping system, Matlab-Simulink*

1. INTRODUCTION

In the field of appropriate thermoregulatory control in pipe systems, the constant growth of cutting-edge technology needs increasingly efficient optimizations to improve application performance. This growing demand highlights the need for more advanced optimization methodologies, motivating researchers to focus their efforts on developing strong optimization algorithms that are customized to the particular problems provided by modern technology applications. Following a thorough survey, it is clear that the immediate applications of optimization techniques in the context of optimal thermoregulatory control extend to a variety of areas, including optimal equipment design, optimal equipment diagnostics, optimal system operation, optimal decision-making under uncertainty, and optimal system planning. These applications act as critical motivators, pushing researchers to develop and expand optimization algorithms, propelling the technology to new heights, particularly in the field of thermoregulatory control in pipe systems.

In the context of thermoregulatory control, optimal equipment design entails meticulously optimizing building procedures to minimize quantity while maximizing uniformity using particular statistical criteria [1–4]. Furthermore, optimum equipment diagnostics, as a subject of control engineering, plays an important role in system monitoring, identifying failure kinds, and detecting faults. The use of optimal equipment diagnostics, particularly in the building of fault classification models, not only improves fault diagnosis accuracy but also decreases training time, allowing for faster recovery of the pipe system by replacing problematic components. The technology's application in the medical industry for automated computer-aided diagnostics complements the overall subject of effective thermoregulatory management in pipe systems. This application aims to remove human mistakes, resulting in more accurate and prompt early detection and treatment of chronic diseases, as demonstrated by computer-aided diagnosis in pathology and radiology.

Optimal system functioning within the context of thermoregulatory control ensures accurate and efficient job performance, often reducing exposure and increasing operational capacity. Simultaneously, optimum decision-making seeks to hedge and maximize average profit while minimizing risk, demanding a thorough examination of profitability analysis, operational efficiency, and realistic possibilities, especially in the context of thermoregulatory management. In contrast, ideal system design for thermoregulatory control entails thorough optimization of construction, equipment layout, material procurement, facility expansion, quality assurance, and cost-effectiveness. This optimization ensures that all components not only meet but exceed user expectations, improving the functioning and integration of subsystem components within the larger context of thermoregulatory control in pipe systems. Recent applications of system planning optimization span a wide range of sectors, including academics, medicine, economics, engineering, politics, and academia, demonstrating its flexibility and significance in optimizing thermoregulatory control systems for pipelines.

Some examples of related technologies include PID (Proportional-Integral-Derivative) controllers, which are commonly used in industrial control systems to regulate process variables like temperature, flow, and pressure; fuzzy logic controllers, which use fuzzy logic to deal with uncertain or imprecise data; neural networks, which are used for adaptive control and complex pattern recognition in systems where mathematical models are difficult to create; and so on. The existing approach has issues with efficiency in optimizing accuracy, handling complexity and ambiguity, and limited flexibility. In very dynamic or non-linear systems, many of the current techniques, such as PID controllers, could not work as well. Complex and uncertain problems can be solved using computationally demanding fuzzy logic and neural networks, which need large amounts of data. To manage ever-increasingly complicated control systems and efficient optimization, there is an ongoing need for algorithms with greater accuracy, resilience, and convergence rates, even if these approaches are typically effective. To overcome these obstacles, this study developed an algorithm for thermoregulation in pipe systems that integrates evolutionary computation with other techniques for better control. We entitled the newly developed algorithm the Memetic Alligator Optimization (MeAgtrO) algorithm, where the term "memetic" stands for a deeper mimicry of the alligator's ecological behaviours in nature from a broader evolutionary perspective. As novelty correlates with major finding, the novelty of MeAgtrO lies in the adoption of novel decision coefficients (satiety), the addition of evolutionary breeding (mating) operators, incorporation of agent replacement (alternation of generation) strategies, the utilization of multi-reference global best solution (scatter hunting) strategies, and the modification of adaptive coefficient (enhanced search behaviours).

When compared to other algorithms, MeAgtrO showed the greatest statistical results in terms of the best, mean, and standard deviation (SD). This is one of the main reasons why MeAgtrO stands out. It performs consistently and reliably well. For control applications in industry, where accuracy and dependability are of the utmost importance, it attained extraordinary resilience, reliability, and accuracy. However, other than that, MeAgtrO demonstrated strong clustering capabilities. If the algorithm does a good job of classifying data or solutions, it should be able to optimize more efficiently and effectively. Among the algorithms that were compared, MeAgtrO had the best convergence rate. In real-time control applications, the algorithm's ability to discover the best solution rapidly is crucial, hence a quicker convergence rate is preferred. When compared to competing algorithms, MeAgtrO appears to have performed better in all important respects that matter much for this particular thermoregulation application in pipe systems. Having these qualities is crucial for optimizing control systems, especially in engineering and industrial settings where dependability and efficiency are paramount. The algorithm was chosen for this investigation because it outperformed others in these critical areas.

This research paper is outlined as follows: Section 1 introduces this research work, Section 2 explains the methodology of the developed MeAgtrO, Section 3 describes the modelling and simulation of control piping system, Section 4 analyses the results, and Section 5 concludes the study.

2. PROPOSED MeAgtrO

The Memetic Alligator Optimization (MeAgtrO) algorithm is proposed as an augmented optimization method for application purposes. It is formulated to execute a search operation that combines the hunting phase and the relocating phase. The overall equation is expressed as follows:

$$\begin{cases} X_i^{t+1} &= X_i^t + F_{1,i}\overrightarrow{V_{hunting_i}}^t + (1 - F_{1,i})\overrightarrow{V_{relocating_i}}^t \\ \overrightarrow{V_{hunting_i}}^t &= \left[\overrightarrow{V_{ps_i}}^t + F_{2,i}\overrightarrow{V_{c_i}}^t\right] \\ \overrightarrow{V_{relocating_i}}^t &= \left[\overrightarrow{V_{t/h_i}}^t + \overrightarrow{V_{w_i}}^t\right] \\ \overrightarrow{V_{PS_i}}^t &= (1 - A)(X_g^t - X_i^t) \\ \overrightarrow{V_{C_i}}^t &= (1 + M)\left(X_g^t - \left(X_i^t + \overrightarrow{V_{ps_i}}^t\right)\right) \\ \overrightarrow{V_{T/H_i}}^t &= (1 - |C|)(2r_1X_{i,lbest}^t - X_i^t) \\ \overrightarrow{V_{W_i}}^t &= \left(1 \pm e^B\left(L(\cos(2\pi B)) + (1 - L)(\sin(2\pi B))\right)\right) \bullet (X_{i,lbest}^t - X_i^t) \end{cases} \tag{1}$$

where $i \in \{1, 2, \dots, N_p\}$ denotes the index of population, N_p is the population number, $t \in \{0, 1, \dots, t_{max} - 1\}$ denotes the index of iteration, t_{max} is the maximum number of iterations, X represents the position point or solution, X_g^t denotes the global best solution that agents (population) had visited so far along the iteration, r_1 is the random number within 0 and 1, $\overrightarrow{V_{hunting_i}}^t$ is a vector representing the hunting phase, $\overrightarrow{V_{relocating_i}}^t$ is a vector representing the relocating phase, $\overrightarrow{V_{PS_i}}^t$ imitates the purse seining behaviour, $\overrightarrow{V_{C_i}}^t$ imitates the catching behaviour, $\overrightarrow{V_{T/H_i}}^t$ imitates the traveling and homing instinct behaviour, $\overrightarrow{V_{W_i}}^t$ imitates the wave vector, $F_{1,i}$ is the hunting flag of the i^{th}agent, $(1 - F_{1,i})$ is the relocating flag opposed to $F_{1,i}$, and $F_{2,i}$ is the catching flag of the i^{th}agent.

For a more refined search mechanism, MeAgtrO proposes the following adaptive coefficients:

$$\begin{cases} A = (2r_2 - 1)\left(1 - \frac{t}{t_{max}}\right)^3 \\ M = e\left(\frac{f(X_{gbest}^t) - f(X_i^t)}{\max(f(X^t)) - \min(f(X^t))}\right) \\ C = 9(2r_3 - 1)\left(1 - \left(\frac{t}{t_{max}}\right)^{3\left(1 - \frac{t}{t_{max}}\right)}\right)^3 \\ B = -9r_4\left(1 - \frac{t}{t_{max}}\right)^3 \end{cases} \tag{2}$$

where r_2, r_3 and r_4 are the random numbers between 0 and 1.

The coefficient adaptation strategy primarily aims to achieve the best results for the global market by refining both global and local search capabilities while smoothing the transition from exploration to exploitation. Coefficient A assigns the possible purse seining distance between the agent (alligator) and the global best solution, toefficient C represents the relocating range towards or away from the home territory (individual local best solution), and coefficient B denotes the pulling force exerted on the agent or the strength of the agent against the wave vector. In MeAgtrO, $\overrightarrow{V_{ps_i}}^t$ becomes the only operator responsible for global exploration and global exploitation, whose characteristics depend on the coefficient A value. The purse seining operation needs to be ideally accelerated. In theory, when the coefficient $|A| > 0.5$, it is more inclined to global exploration, and conversely, when the coefficient

$|A| \leq 0.5$, it is more inclined to global exploitation. Given that agents require fewer iterations to stabilize, while ensuring that they do not skip any search types throughout their execution, the maximum available value of coefficient A is gradually tapered off at a faster rate to effectively speed up the transition from exploration to exploitation. The faster pace of purse seining behavior now allocates less global exploration and more global exploitation, resulting in a more desirable trade-off between global exploration and global exploitation. By contrast, the coefficient C is adapted to have a slower declination velocity to ensure that the agents can have enough iterations to process the local search operation, giving them more opportunities to escape local optima while searching for any possible global optimal region. Depending on the situation, this approach can positively speed up convergence or negatively hinder optimization output. The coefficient B is thereby adapted to have a quicker reduction, just to synchronize to some extent to cover (balance) the negative effect caused by the coefficient C. Overall, the adaptation of these important coefficients is expected to achieve better optimization efficiency.

2.1. Satiety Awareness

The search agent decides whether to enter the hunting or relocation phase during execution. For more reliable decision-making methods instead of random selection, MeAgtrO proposes decision-making approaches based on a novel decision coefficient S, where S theoretically represents the satiety of the agents (alligators). S_i^t, on the other hand, can be denoted as the satiety coefficient of the i^{th} agent at the t^{th} iteration. MeAgtrO utilizes S_i^t to control the selection methods of the i^{th} agent in a smarter way, mainly via $F_{1,i}$ and $F_{2,i}$, which can be expressed mathematically as follows:

$$\begin{cases} F_{1,i} = \begin{cases} 1, & \text{if } S_i^t \leq r_1 \\ 0, & \text{otherwise} \end{cases} \\ F_{2,i} = \begin{cases} 1, & \text{if } S_i^t \leq r_1 \text{ and } i \in J \\ 0, & \text{otherwise} \end{cases} \\ S_i^{t+1} = e^{(-r_5 S_i^t)} \end{cases} \tag{3}$$

where:

$$\begin{cases} J \in \{i_{R\{1\}}, i_{R\{2\}}, \dots, i_{R\{N_s\}}\} \\ N_s = \left\lfloor \text{length}\left(\text{find}(S_{\text{sorted}}^t > 0)\right)/4 \right\rfloor \\ R = \text{find}(S_{\text{sort}}^t > 0) \\ S_{\text{sort}}^t = \underset{\text{ascend}}{\text{sort}}\left(F_{1,1\to N_p}^t \bullet S_{1\to N_p}^t\right) \end{cases} \tag{4}$$

where $e^{(-r_5 S_i^t)}$ returns the exponential value, S_{sort}^t denotes satiety values sorted in ascending order which corresponds to search agents sorted from lowest satiety to highest satiety, R is a function that identifies the index of the search agent that satisfies the condition $S_{sort}^t > 0$ (by which search agents that do not execute $\overrightarrow{V_c}$ at the t^{th} iteration will be excluded), N_s is the estimated number of hunting agents allowed to be included in executing $\overrightarrow{V_c}$ at that iteration, and J represents the index of the search agent that is finally qualified to execute $\overrightarrow{V_c}$ after rounds of selection.

The initial coefficient value of S_i^t is 1. When $S_i^t \approx 1$, it indicates that the i^{th} agent is full, and when $S_i^t \approx 0$, it indicates that the i^{th} agent is starving. From mathematical perspective, S_i^t gradually decreases with iterations, simulating the fact that creatures lose their satiety over time if they do not feed. The decreasing degree of $\mathrm{S_i^t}$ can refer to Equation (3). Extending the explanation, this coefficient plays an important role in deciding whether the i^{th} agent biases the hunting phase or the relocating phase, indirectly via $F_{1,i}$. It should be noted from the formula of $F_{1,i}$ that the smaller the value of the coefficient S_i^t, the greater the chance of the i^{th} agent to select the hunting phase. This brings up another implication that the agent urgently needs to restore its satiety. Overall, this coefficient S can actually assign a perfect balance of trade-offs between the hunting phase and the relocation phase in any given optimization problem. It maintains the systematic characteristics to some extent, but at the same time inherits the minimal required randomness, which is more capable to decide which favourable phase to enter according to the current situation. The main concept, in turn, allows the agents (alligators) to regain satiety from feeding, forcing the agent to leave the hunting phase and enter the relocating phase at the next iteration. Mathematically, the i^{th} agent that executed the catching mechanism ($\overrightarrow{\boldsymbol{V}}_{\mathrm{c}_i}^{t}$) restores satiety, thereby resetting S_i^{t+1} to 1. But as specified, only a small fraction (usually ¼ fraction) of agents can perform the catching mechanism in one iteration, hardly imitating the fact that alligators systematically "take turns" while catching prey in sequence. To more faithfully mimic alligators as social predators that tolerate each other while hunting, F_2 rationally assigns agents with lower satiety to have a greater chance of preferentially executing catching behavior in Equation (3). The proposed decision-making or selection method using this novel decision coefficient (S) is expected to achieve better optimization performance in terms of global best results and convergence speed.

2.2. Mating

Inspired by the biological reproduction process, MeAgtrO proposes to add on an evolutionary breeding operator. For the breeding purpose, the algorithm separates population into half male ($\mathrm{X}^{\mathrm{t}}_{1\to \mathrm{N_p}/2}$) and half female ($\mathrm{X}^{\mathrm{t}}_{1+\mathrm{N_p}/2\to \mathrm{N_p}}$). At the beginning of each iteration, the agents execute breeding operations, simulating the arrival of the mating season. From a mathematical point of view, the breeding operator allows for the crossover of information between agents of different genders, which adds an extra step to the algorithm to generate a bunch of talented offspring that inherit the predominant (genetic) information. Agents of different genders selected to execute the breeding operation are referred to as parents. For the next breeding step, all solutions of the offspring are mutated to a certain extent to adapt to the global best solution (i.e., the hunting ground). The proposed breeding operation can be expressed mathematically as follows:

$$\begin{cases} \mathrm{X}^{\mathrm{t}}_{\mathrm{off,gh}} &= (\vec{\mathrm{r}}_1 \geq 0.2)\bullet \mathrm{X}^{\mathrm{t}}_{\mathrm{cross,gh}} + (\vec{\mathrm{r}}_1 < 0.2)\bullet \mathrm{X}^{\mathrm{t}}_{\mathrm{mutate,gh}} \\ \mathrm{X}^{\mathrm{t}}_{\mathrm{mutate,gh}} &= \mathrm{X}^{\mathrm{t}}_{\mathrm{gbest}} + \xi\left|\mathrm{X}^{\mathrm{t}}_{\mathrm{cross,gh}} - \mathrm{X}^{\mathrm{t}}_{\mathrm{gbest}}\right| \\ \mathrm{X}^{\mathrm{t}}_{\mathrm{cross,gh}} &= (\vec{\mathrm{r}}_2 \leq 0.5)\bullet \mathrm{X}^{\mathrm{t}}_{\mathrm{g}} + (\vec{\mathrm{r}}_2 > 0.5)\bullet \mathrm{X}^{\mathrm{t}}_{\mathrm{h}} \\ \xi &= 1 - \mathrm{e}^{\left(-\left(\frac{1-\mathrm{t}}{\mathrm{t_{max}}}\right)^3\right)} \end{cases} \tag{5}$$

where $\vec{\mathrm{r}}$ is the random array within 0 and 1, $|\cdot|$ denotes the absolute function, $\mathrm{X}^{\mathrm{t}}_{\mathrm{g}} \in \left\{\mathrm{X}^{\mathrm{t}}_{\mathrm{i}=1}, \mathrm{X}^{\mathrm{t}}_{\mathrm{i}=2}, \dots, \mathrm{X}^{\mathrm{t}}_{\mathrm{i}=\mathrm{N_p}/2}\right\}$ is the g^{th} male agent at t^{th} iteration, $\mathrm{X}^{\mathrm{t}}_{h} \in \left\{\mathrm{X}^{\mathrm{t}}_{\mathrm{i}=1+\mathrm{N_p}/2}, \mathrm{X}^{\mathrm{t}}_{\mathrm{i}=2+\mathrm{N_p}/2}, \dots, \mathrm{X}^{\mathrm{t}}_{\mathrm{i}=\mathrm{N_p}}\right\}$ is the h^{th} female agent at t^{th} iteration, and $\mathrm{X}^{\mathrm{t}}_{\mathrm{off,g}h}$ is the final offspring solution reproduced by the g^{th} male agent and the h^{th} female agent at t^{th} iteration. Note that agents of different genders that have been selected as parents will not be selected again for the upcoming crossover processes at one iteration, which mean that the selected g^{th} male agent and h^{th} male agent will not be selected as the next parent candidates for consecutive crossover processes at the same iteration. This concept ensures that every agent can become a parent candidate without being excluded or duplicated. For rational selection, g is selected based on the normal cumulative distribution of $\underset{\text{ascend}}{\text{sort}}\left(f\left(X^t_{1\to N_p/2}\right)\right)$, while h is selected based on the normal cumulative distribution of $\underset{\text{ascend}}{\text{sort}}\left(f\left(X^t_{1+N_p/2\to N_p}\right)\right)$. In a more specific way of interpretation, the breeding operator includes crossover and mutation processes. Referring to Equation (5), offspring theoretically inherit about 80% of the crossover information from the parents and develop about 20% of the mutational information. During the crossover process, it generates the new offspring by exchanging the information of two agents from different assigned genders, where the dimensional information represents the genes of the agents. This crossover of dimensional information has improved the escape ability of agents from the local optima to some extent, at the same time, covering any insufficiency in exploration operations. In theory, the male and female agents are both queue in an ascending order from best-performed to poorest-performed units. The selection is said to highly depend on the current fitness of the agents, as the agents select their partner via the normal cumulative distribution approach, where upper ranked units are more likely to select the upper ranked partner from different gender in the breeding operation. The crossover process between well-behaved agents (from different genders) is thought to produce offspring that inherit promising dimensional information that contributes to local absconding skills, global proximity, and accelerated progression. The crossover process is followed by the mutation process. The mutation process replaces approximately 20% of the content in the offspring solution (post-crossover) with global best information that deviates from the fluctuation range. This slightly diverges the offspring solution from the parent solutions, bringing the offspring closer to the prey positions to facilitate participation in the next hunting phase. Mathematically, the mutation process adds fluctuations and oscillations in terms of flexibility, accelerating the optimization process by refining exploration operations.

2.3. Alternation of Generation

Offspring generated from equation (5) are randomly assigned gender (either male or female). In MeAgtrO, every offspring can potentially replace the position point of its parent of the same gender if a better solution is provided. This is thought to eliminate less efficient solutions from the population to speed up the optimization process (convergence rate), and to some extent provide potential escape routes for the population to escape from local optima. Despite the little extra computational time spent during the comparison process, this approach is highly appreciated because the newly generated offspring inheriting better information can benefit greatly in the next search operation, potentially reaching a more optimal region, thereby guiding the entire population towards a better global best solution. This ultimately strengthens the clustering properties of the algorithm. Upon formulation, the agent replacement strategy at the t^{th} iteration can be expressed as:

$$\begin{cases} X^t_g = \begin{cases} X^t_g & \text{, if } r_6 \le 0.5 \text{ and } f(X^t_g) < f(X^t_{off,gh}) \\ X^t_{off,gh} & \text{, otherwise} \end{cases} \\ X^t_h = \begin{cases} X^t_{off,gh} & \text{, if } r_6 > 0.5 \text{ and } f(X^t_h) < f(X^t_{off,gh}) \\ X^t_h & \text{, otherwise} \end{cases} \end{cases} \tag{6}$$

When a new offspring is spawned and replaces its parent, its satiety ($S^t_{i=g|h}$) restarts from a full number 1, but does not inherit the satiety of its replaced parent, as both are considered to be independent units. In contrast, offspring that replace its parent will inherit the local best solution ($X^{t+1}_{i=g|h,lbest}$) to mimic the "home" of the designated parent candidate passed to its descendant. This is what is called inheriting the achievements of the older generation, benefiting the younger generation regardless of living conditions. However, if there is a better solution, it mathematically updates its current position point to the local best solution during the initial fitness comparison.

2.4. Scatter Hunting

There should usually be more than one prey in the natural environment. As for a more faithful imitation, a multi-reference position seems necessary. Therefore, a multi-reference global best solution strategy is proposed in MeAgtrO, which prepares four selectable prey positions ($X_{gbest} \in \{X_{gbest(1)}, X_{gbest(2)}, X_{gbest(3)}, X_{gbest(4)}\}$) for the population. Each agent randomly defines its global best solution from these four candidates, where the probability of selecting any one is ¼. The agents update solutions from $X_{gbest(1)}$ to $X_{gbest(4)}$ in ascending order: if a solution is found better than $X_{gbest(1)}$, $X_{gbest(1)}$ is replaced by that solution, otherwise it moves on to compare that solution with $X_{gbest(2)}$, and so on. The multi-reference global best solution can theoretically disperse the agents to the respective prey positions, thereby expanding the search range of the agents, mainly for more effective and efficient global exploration in the early stage of iteration. Though it is estimated that prey positions ($X_{gbest(1\rightarrow 4)}$) will gradually cluster along the iterative update. These somewhat improve the performance in terms of global best results and convergence speed.

The following pseudocode presents the entire mechanism of MeAgtrO:

```
Input parameters
Initialize population (agents)
Calculate the objective fitness values for all agents
t = 0;
X^t_gbest(1→4) = best agent solutions
X^t_1→Np,lbest = X_1→Np
WHILE (t < t_max)
    FOR i = 1 TO Np/2
        Evolutionary breeding operation: Equation (5)
        Agent replacement strategy: Equation (6)
    END FOR
    Population satiety: Equation (3)
    FOR i = 1 TO Np
        Adaptive coefficients: Equation (2)
        Search operational mechanism: Equation (1)
        Calculate the objective fitness value of i^th agent
```

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Replace $X^t_{i,lbest}$ if i^{th} agent has a better solution

END FOR

Replace $X^t_{gbest(1\rightarrow 4)}$ in sequence if any agent provides a better solution

$X^{t+1}_{gbest(1\rightarrow 4)} = X^t_{gbest(1\rightarrow 4)}$

$X^{t+1}_{1\rightarrow N_p,lbest} = X^t_{1\rightarrow N_p,lbest}$

$t = t + 1$

END WHILE

Global best objective fitness value = $f\left(X^{t=t_{max}}_{gbest}\right)$

Output $X^{t=t_{max}}_{gbest}$

Output $f\left(X^{t=t_{max}}_{gbest}\right)$

3. SIMULATION OF THERMOREGULATION IN PIPING SYSTEMS

For simulation, the model of the piping system is customized while referring to the literature [5]. The entire layout of the simulated piping system is displayed in Figure 1, consisting of water tank, heat exchanger, thermocouple, controller, gate valve, pipe, and wire. For a clearer image, Figure 2 shows an enlarged image of these widgets.

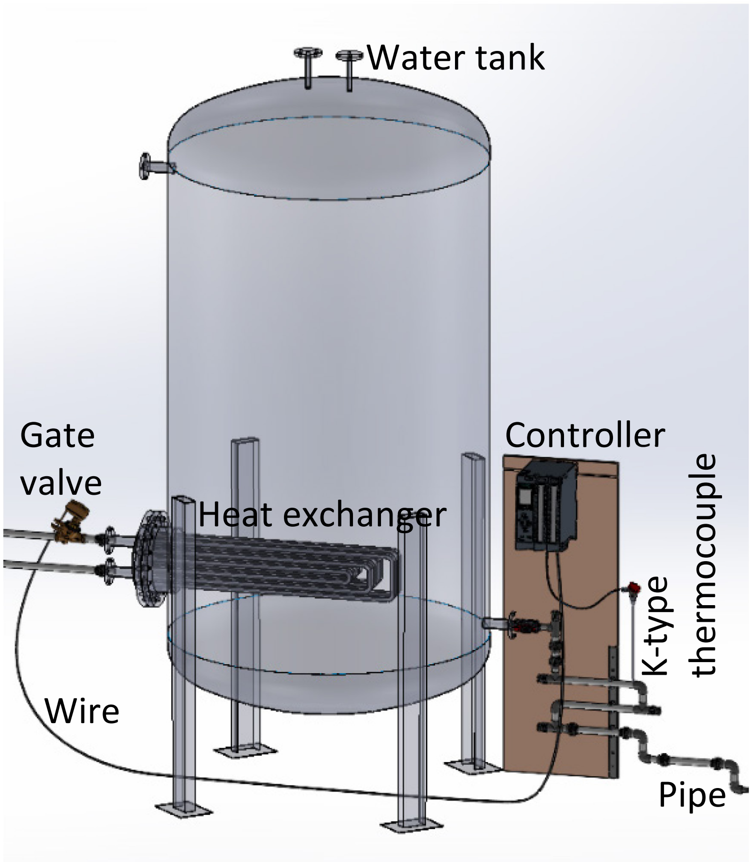

Figure 1. Layout of simulated piping system

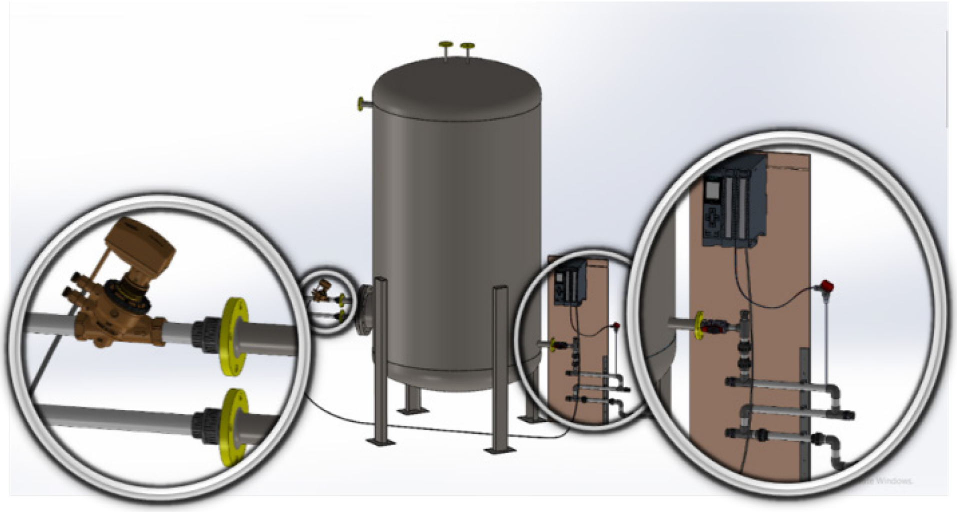

Figure 2. Enlarged layout of simulated piping system

The steam heater exchanger supplies sustainable heat to the fluid in the storage tank, while the fluid in the storage tank will flow to other equipment through the pipeline. The main objective of the simulation is to get the fluid in the pipe to reach and maintain the desired temperature. This is the so-called thermoregulation process. Considering the mathematical heat loss, the temperature of the fluid in the pipes is not exactly equal to the temperature in the tank. There are basically three types of heat loss: conduction, convection, and radiant heat loss that occur in the pipeline. These heat losses are strongly affected by the material and thickness of each composed layer in the insulated pipe. Therefore, the material selection of insulated pipeline must consider various factors, including its thermal insulation, electrical conductivity and corrosion resistance [6]. All composed material details can be reviewed from related articles and book chapters [7, 8]. For simulation, we constructed a pipeline consisting of a layer of fiberglass insulating protective cover and copper tubing. For ease of understanding, Figure 3 displays a cross-sectional view of the constructed insulated pipe, and Figure 4 illustrates the mechanism of the heat transfer process in this insulated pipe.

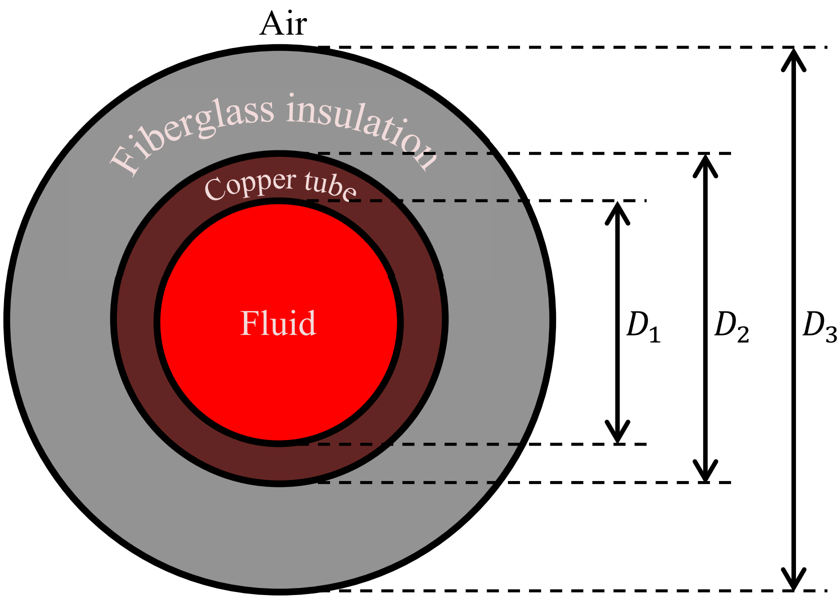

Figure 3. Cross-sectional view of insulated pipeline

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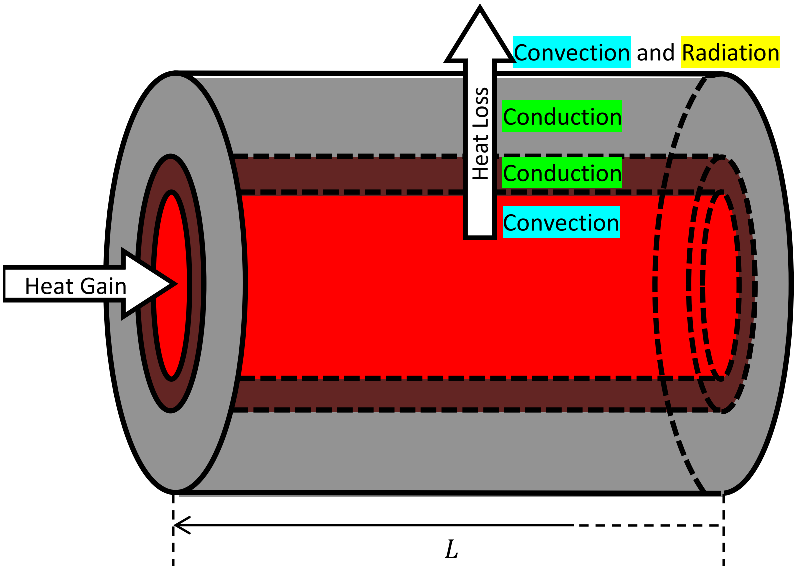

Figure 4. Mechanism of heat transfer process in insulated pipeline

From a mathematical perspective, due to net heat transfer, the operating temperature of the fluid inside the pipe in the time series domain can be expressed as:

$$T_{op}(\dot{t} + \dot{t}_{interval}) = T_{op}(\dot{t}) + \int_{0}^{\dot{t}_s=1} \frac{1}{\rho V c}\left[C_p T_{in}(\dot{t}) + \left(\frac{T_{op}(\dot{t}) - T_a(\dot{t})}{\frac{\mathrm{In}(D_2/D_1)}{2\pi L k_{tube}} + \frac{\mathrm{In}(D_3/D_2)}{2\pi L k_{insulation}} + \frac{1}{(\pi D_3 L)h_{air}} + \frac{1}{(\pi D_1 L)h_{fluid}}}\right)\right] d\dot{t} \tag{7}$$

where T represents the temperature, and hence T_{op} is the operating temperature of the fluid (unit: K) and T_{in} is the input temperature of the fluid when entering the pipe (unit: °C). $\dot{t} \in \{0, \dot{t}_{interval}, 2\dot{t}_{interval}, \dots, \dot{t}_{end}\}$ represents the index of time, where $\dot{t}_{end}$ is the simulation duration (unit: s), $\dot{t}_{interval}$ is the time interval per update (unit: s), and $\dot{t}_s$ is the timespan. Supposed that the fluid in the entire L-length pipe shares the same temperature of T_{op}, where T_{op} is initialized to T_a when $\dot{t} = 0$. During simulation, $t_{interval} = 0.01$ and $t_{end} = 10$, which allows the system to update the operating temperature every 0.01s from 0s to 10s. For convenience of explanation, the definitions and values of the remaining parameters are displayed in Table 1.

The simulated piping system designed for thermoregulation application is considered a feedback control system. To ensure that the fluid maintains the desired temperature when it reaches the desired point in the pipeline, a k-type thermocouple is placed at any corner end of the L-length pipeline, acting as a sensor to acquire temperature data at that point. The wire sends the information data obtained from the thermocouple to the controller. The controller computes the temperature difference and the percentage error, which then tunes the parameters and sends the signal out to the gate valve. After receiving the command signal from the controller, the gate valve adjusts the steam flow rate in the heat exchanger and the heat supplied to the water tank, thereby regulating the temperature of the fluid in the water tank. Note that the controller installs the specified optimization algorithm to handle the process of parameter optimization. The optimization process is repeated for a given number of iterations until the piping system reaches its optimal thermoregulation performance.

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Table 1. Detailed parameters in the pipeline

	Indicator	Description	Value	Unit
Pipeline				
	$\boldsymbol{L}$	Length of insulated pipeline	0.1	m
Fiberglass insulation				
	$\boldsymbol{D_3}$	Outer diameter of insulation	0.1889	m
	$\boldsymbol{k_{insulation}}$	Thermal conductivity of insulation	0.04	$W/_{mK}$
Copper tube				
	$\boldsymbol{D_1}$	Inner diameter of copper tube	0.0779	m
	$\boldsymbol{D_2}$	Outer diameter of copper tube	0.0889	m
	$\boldsymbol{k_{tube}}$	Thermal conductivity of copper tube	385	$W/_{mK}$
Fluid				
	$\boldsymbol{h_{fluid}}$	Heat transfer coefficient of fluid	100	$W/_{m^2K}$
	$\boldsymbol{\rho}$	Density of fluid	997	$kg/_{m^3}$
	$\boldsymbol{V}$	Volume of fluid	$\pi L\left(\frac{D_1}{2}\right)^2$	m^3
	$\boldsymbol{c}$	Specific heat capacity of fluid	4200	$J/_{kgK}$
Air				
	$\boldsymbol{h_{air}}$	Heat transfer coefficient of air	10	$W/_{m^2K}$
	$\boldsymbol{T_a}$	Ambient temperature	296.15	K
Input				
	$\boldsymbol{C_p}$	heat input coefficient	250	$W/_{°C}$

In a more specific explanation, the controller employs the concept of proportional-integral-derivative (PID). It is a feedback control loop mechanism [9–11] that continuously tunes the signal to be output to the gate valve while processing the negative feedback input from the thermocouple until the ideal zero error is obtained. We define u as the control signal fed into the gate valve for regulation, where u generated by the PID concept is computed in the time domain using the following expression [12]:

$$\begin{cases} u(t) = K_p\varepsilon(t) + K_i\int\varepsilon(t)\,dt + K_d\frac{d\varepsilon(t)}{dt} \\ \varepsilon(t) = T_{set} - T_{op}(t) \end{cases} \tag{8}$$

where T_{set} denotes the desired temperature (set point) of the fluid in the pipe and T_{op} denotes the operating temperature (feedback input from thermocouple) of the fluid in the pipe, where T_{set} is constantly set to $100°C$ throughout the simulation. ε represents the tracking error, which defines the error difference between the set point (desired temperature, T_{set}) and the feedback input (temperature measured by the thermocouple, T_{op}). $K = [K_p, K_i, K_d]$ is a set of control variables of the optimization algorithm, where K_p is the proportional gain, K_i is the integral gain, and K_d is the derivative gain. Each coefficient gain corresponds to each variable: K_p times the magnitude of ε, K_i times the integral of ε, and K_d times the derivative of ε. After numerous preliminary tests, it was determined that $-300 \leq K_p \leq 300$ and $-50 \leq K_i, K_d \leq 50$ are most appropriate for the system's characteristics. Indeed, all gains lie within theoretically convincing ranges, with positive upper and negative lower bounds to accommodate controls of the opposite sign. K_p as a proportional gain is set to the widest possible range to allow massive amplification of the signal amplitude, thereby achieving faster processing response. In contrast, shorter ranges work well for K_d and K_i, as they require fine-tuning to control linear distortion and distal term error respectively, but excessively narrow ranges are prohibited, as K_d and K_i must provide all conceivable combinations. Figure 5 visually explains the mechanism in the controller when the optimization algorithm is applied. The application of the optimization algorithm to the tuning process is expected to yield better performance in a step response, primarily by increasing the speed at which the set point threshold is reached and reducing the percentage of overshoot (or undershoot) relative to the set point. Hence, the objective fitness of an optimization algorithm is given as follows:

$$\min f(K) = (1 + |\varepsilon(\dot{t}_{end})|)(R_t + S_t + O_s + U_s) \quad (9)$$

where $\varepsilon(\dot{t}_{end})$ also represents the steady-state error of the step response, R_t represents the rise time, S_t represents the settling time, O_s represents the percentage overshoot, and U_s represents the percentage undershoot. By definition, rise time is the time required for the T_{op} response to rise from 10% to 90% of the steady-state response (T_{set}), and settling time is the time required for the T_{op} response to reach and remain within 2% of the steady-state response (T_{set}). The system's damping ratio indicates whether a system is likely to overshoot or undershoot. A system that is over-damped will undershoot its target value. Conversely, an under-damped system will overshoot its target value. Figure 6 illustrates these quantities in a typical step response plot. The minimal fitness that the algorithm can achieve will determine its optimal performance in this optimization application. Overall, the smaller the fitness value an algorithm can achieve, the better the algorithm performs in this application.

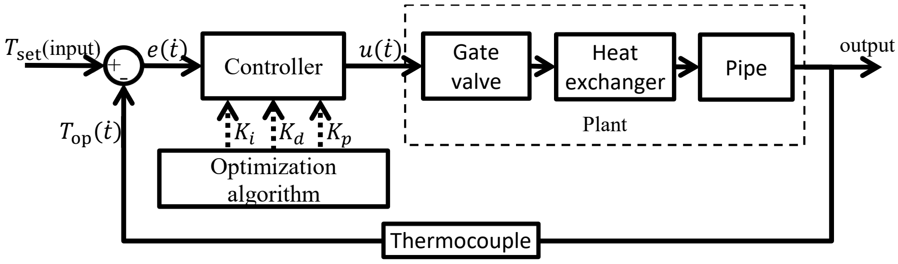

Figure 5. Layout of thermoregulation control system

During the evaluation process, the proposed MeAgtrO and other comparative algorithms (including Alligator Optimization (AgtrO) algorithm [13], Reptile Search Algorithm (RSA) [14], Pelican Optimization Algorithm (POA) [15], Aquila Optimizer (AO) [16], Arithmetic Optimization Algorithm (AOA) [17], Dingoes Optimization Algorithm (DOA) [18], Social Ski Driver (SSD) algorithm [19], and Seagull Optimization Algorithm (SOA) [20]) were installed in the controller in turn to examine and compare the performance of each algorithm in this application. The algorithms chosen for comparison with MeAgtrO were based on the following considerations: AgtrO was chosen as it is the basic algorithm of MeAgtrO. In addition, only state-of-the-art algorithms were considered, among which only algorithms proposed within the last 5 years were selected as comparative algorithms. In fact, AgtrO was proposed in 2023, RSA and POA were proposed in 2022, AO, AOA and DOA were proposed in 2021, SSD was proposed in 2020, and SOA was proposed in 2019. For fair comparison, all comparative algorithms were only selected from the same school of population-based optimization and a category of nature-inspired optimization. The fact that they are standard optimizers was also a crucial factor in their selection as candidates, which makes it easier to assess how better improved MeAgtrO variations affect the application. The parameter settings of all algorithms are set to default, as stated in Table 2, to ensure an equitable comparison in performance. 10 simulation runs were conducted for the application of each algorithm to facilitate robust statistical analysis and result comparison. Given the problem definition, $t_{max} = 50$ and $N_p = 50$ per simulation run.

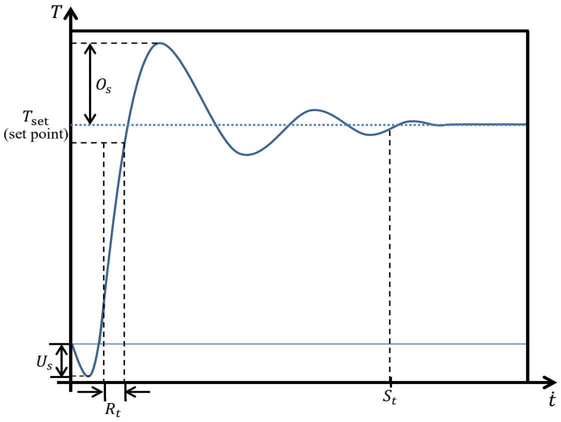

Figure 6. Typical step response

Table 2. Detailed parameters in the pipeline

Parameter	Range or value
MeAgtrO	
—	—
AgtrO	
α	$[0, 1]$
β	$[0, 1]$
δ	$[0, 20]$
γ	$[-50, 0]$
RSA	
α	0.1
β	0.005
POA	
—	—
AO	
α	0.1
δ	0.1
u	0.0265
r_0	10
ω	0.005
φ_0	$3\pi/2$
AOA	
MOP_{max}	1
MOP_{min}	0.2
α	5
μ	0.499
DOA	
P	0.5
Q	0.7
N_{init}	2
N_{end}	N_p/N_{init}
N	$\lfloor N_{init} + (N_{end} - N_{init})r \rfloor$
SSD	
a	$[0, 2]$
SOA	
F_c	$[0, 2]$
b	1

4. RESULTS AND DISCUSSION

In this section, we compare and analyse the optimal control performance of MeAgtrO (for thermoregulation applications in piping system) against other comparative algorithms based on different collected data.

Table 3 collects the statistical f(K) results obtained by all the evaluated algorithms in the thermoregulation application. The statistics include three evaluation matrices such as the best, mean, and standard deviation (SD) results for every tested algorithm. Knowing that the objective f(K) fitness (refer Equation (9)) is specified for minimization, the superiority on the corresponding evaluation matrices will reveal the respective characteristics of the algorithms in minimizing tracking error, response time, and equipment burden. More specifically, the accuracy, reliability and robustness of the algorithm for solving this optimal control application can be determined by the statistical best, mean and SD results, respectively.

By statistically comparing the best results, it can be noticed that MeAgtrO, AgtrO, POA, POA and SOA achieved the minimum optimality. AO ranked second with excellent statistical best results but slightly worse than these 5 algorithms, followed by RSA in third, AOA in fourth, and finally SSD in fifth. Here, we can analyse that MeAgtrO, AgtrO, POA, DOA and SOA are equally outstanding in terms of accuracy, and definitely outperform the remaining 4 algorithms. By converting the statistical best results into measurable indications, we can clarify that, while the accuracy of RSA, AOA and SSD is insignificant, the accuracy of MeAgtrO, AgtrO, POA, DOA, and SOA is all 100%, which is 43.33% greater than the accuracy of AO.

MeAgtrO ranked first on statistical mean, followed by AgtrO that ranked second, then AO, SOA, DOA, SSD, POA, AOA and RSA that ranked third to ninth respectively. Upon analysis, MeAgtrO, which obtained the most superior statistical mean results, is proven to be the most precise algorithm, while RSA is proven to be the least precise. It is also worth noting that the mean result for MeAgtrO is exactly equal to its best result, indicating that MeAgtrO could reach global minimum in every simulation run. This demonstrates MeAgtrO's consistency in tracking set points (i.e., required temperatures) in optimal control applications for piping system, which saves training costs and time in mechanical processes. From the measurement point of view, the reliability performance of MeAgtrO reaches about 100%, which is 1.11% higher than AgtrO, 2.29% higher than AO, 4.17% higher than SOA, 9.34% higher than DOA, 12.83% higher than POA, 29.96% higher than SSD, etc.

With great consistency comes a great standard deviation (SD) result. Note that the optimal value of SD is zero, where an SD result of zero indicates perfect robustness of the algorithm during the optimization processes. Among all comparative algorithms, only MeAgtrO could obtain statistical SD result that is extremely close to zero value. Without a doubt, MeAgtrO achieved the outperforming SD results in optimal thermoregulatory control applications. Even the second-ranked AgtrO could only achieve an SD result that is at least 106 times behind MeAgtrO; not to mention others that are much worse than AgtrO on SD results. To demonstrate the actual performance difference in terms of measurable robustness, we declare that MeAgtrO is nearly 100% robust, 1.23% better than AgtrO, 1.59% better than AO, 13.01% better than SOA, 15.58% better than DOA, 17.46% better than POA, and 18.28% better than SSD. On the contrary, AOA and RSA have approximately 0% robustness. From mere statistics, MeAgtrO has proven its outperformance in terms of accuracy, reliability, and robustness when dealing with optimal thermoregulatory control applications. All these claims support the fact that MeAgtrO can minimize tracking errors, response times, and equipment burden with minimal training runs.

Table 3. Complete results of adopted algorithms for thermoregulation application in simulated piping system

Algorithms	Ind.	1st run	2nd run	3rd run	4th run	5th run	6th run	7th run	8th run	9th run	10th run	Best	Mean	SD
MeAgtrO	K_d	-0.43	-0.14	-0.33	0.65	-0.28	0.24	-0.15	-0.32	0.59	0.79			
	K_p	154.41	154.91	154.80	154.50	154.34	154.67	154.55	154.71	154.13	154.32			
	K_i	0.39	-0.12	0.00	0.30	0.46	0.12	0.24	0.09	0.66	0.48			
	$f(K)$	1.39E+00	1.39E+00	1.39E+00	1.39E+00	1.39E+00	1.39E+00	1.39E+00	1.39E+00	1.39E+00	1.39E+00	**1.39E+00**	**1.39E+00**	**2.72E-07**
AgtrO	K_d	11.40	-3.60	-0.84	1.02	12.69	1.13	1.76	13.11	2.09	-11.55			
	K_p	153.91	139.33	150.95	154.55	153.92	153.89	153.87	153.93	153.83	117.14			
	K_i	0.89	0.60	0.75	0.25	0.88	0.91	0.92	0.86	1.11	0.21			
	$f(K)$	3.37E+00	2.34E+00	1.50E+00	1.39E+00	3.37E+00	1.39E+00	1.39E+00	3.37E+00	1.58E+00	3.99E+00	1.39E+00	2.37E+00	1.05E+00
RSA	K_d	0.00	0.79	0.00	0.00	0.00	0.00	0.00	0.00	-0.05	0.73			
	K_p	0.00	151.19	0.00	0.00	0.00	0.00	0.00	0.00	149.99	145.70			
	K_i	0.00	0.44	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00			
	$f(K)$	6.55E+04	2.01E+00	6.55E+04	6.55E+04	6.55E+04	6.55E+04	6.55E+04	6.55E+04	2.33E+00	3.02E+00	2.01E+00	4.59E+04	3.17E+04
POA	K_d	24.76	0.61	-0.44	-1.10	-12.68	4.97	-11.37	-13.44	0.67	31.35			
	K_p	144.38	153.52	151.83	112.02	184.74	154.73	93.19	130.00	153.93	140.97			
	K_i	27.67	0.09	0.81	1.30	1.09	-0.13	0.82	-0.02	0.60	27.84			
	$f(K)$	3.84E+01	1.40E+00	1.40E+00	6.63E+00	1.87E+01	4.26E+00	6.15E+00	8.34E+00	1.39E+00	4.01E+01	1.39E+00	1.27E+01	1.49E+01
AO	K_d	-0.30	-19.27	15.46	-2.08	8.35	-4.79	-18.06	14.38	-14.28	0.59			
	K_p	154.22	88.32	149.26	155.72	153.63	140.39	99.70	149.64	105.37	153.98			
	K_i	1.33	0.55	1.31	-0.19	0.81	0.06	0.13	1.08	0.12	0.88			
	$f(K)$	2.03E+00	5.74E+00	3.92E+00	2.08E+00	3.36E+00	2.79E+00	4.90E+00	3.66E+00	4.19E+00	1.42E+00	1.42E+00	3.41E+00	1.36E+00
AOA	K_d	0.00	3.86	0.00	-0.95	-28.96	-1.07	0.00	-0.03	0.00	15.67			
	K_p	0.00	130.47	0.00	150.40	352.48	334.48	0.00	167.79	0.00	150.15			
	K_i	0.00	32.62	0.00	0.00	-1.94	0.00	0.00	-0.30	0.00	21.07			
	$f(K)$	6.55E+04	4.45E+01	6.55E+04	2.12E+00	1.04E+02	1.00E+02	6.55E+04	8.55E+00	6.55E+04	3.65E+01	2.12E+00	2.62E+04	3.38E+04
DOA	K_d	-0.83	-0.23	-1.00	21.98	25.71	-4.56	-0.07	-38.30	-1.14	27.84			
	K_p	153.68	152.13	154.95	198.19	147.40	128.63	148.16	47.64	154.21	148.49			
	K_i	0.93	0.07	-0.16	-0.03	19.96	1.00	0.52	0.32	-0.06	0.37			
	$f(K)$	1.99E+00	1.41E+00	1.39E+00	3.04E+01	3.80E+01	3.37E+00	2.30E+00	8.81E+00	1.39E+00	7.11E+00	1.39E+00	9.62E+00	1.33E+01
SSD	K_d	18.80	-9.73	-4.70	15.33	11.42	-21.10	1.80	-7.71	4.62	9.88			
	K_p	124.92	91.70	67.85	134.50	151.41	73.59	120.72	122.43	123.06	154.22			
	K_i	20.79	10.61	10.19	20.31	17.90	9.60	12.67	12.38	0.89	18.69			
	$f(K)$	3.87E+01	1.31E+01	4.48E+01	3.34E+01	2.07E+01	4.12E+01	3.20E+00	4.02E+01	6.15E+00	3.67E+01	3.20E+00	2.78E+01	1.56E+01
SOA	K_d	0.14	12.81	-1.57	0.12	0.66	-0.93	-0.28	-1.37	0.75	-0.19			
	K_p	154.28	155.94	146.95	154.14	154.62	151.98	153.83	152.06	153.78	153.76			
	K_i	0.52	17.85	0.68	0.57	0.15	0.40	0.52	0.74	0.49	0.67			
	$f(K)$	1.39E+00	3.67E+01	2.20E+00	1.39E+00	1.39E+00	1.40E+00	1.39E+00	2.03E+00	1.39E+00	1.39E+00	1.39E+00	5.07E+00	1.11E+01

The convergence plot is displayed in Figure 7. It plots the means of the objective fitness calculated in Equation (9) for all algorithms in every iteration. Due to the high simulation load, the convergence data was collected from an average of 10 simulation runs, but this amount of simulation runs is believed to produce reliable results. Theoretically, algorithms that converge and stabilize in earlier iterations in the curve are considered to have better convergence rate. Hence, we exclude RSA and AOA that did not show any observable convergence, as their deficiencies are obvious in convergence evaluation. POA barely converged at the beginning of the iteration until the 19–20th iteration, indicating that the convergence rate is slow to begin with. While AO, ROA, DOA and SOA started to converge before the 5th iteration, they only reached stability after the 40th iteration, so it is difficult to claim that they have good convergence speed. AgtrO fared slightly worse as it reached stability in the last 10 iterations but began to converge around the 9th iteration. In contrast, the MeAgtrO curve began to converge from the beginning of iterations, gradually reached the minimum fitness, and stabilized at 20th iterations. Through analysis and comparison, it can be clearly seen that MeAgtrO has a stronger and faster convergence speed. Also, it is obvious that MeAgtrO could attain more minimal global best objective fitness. These findings support the claim that MeAgtrO has the best processing efficiency during optimization for thermoregulation applications.

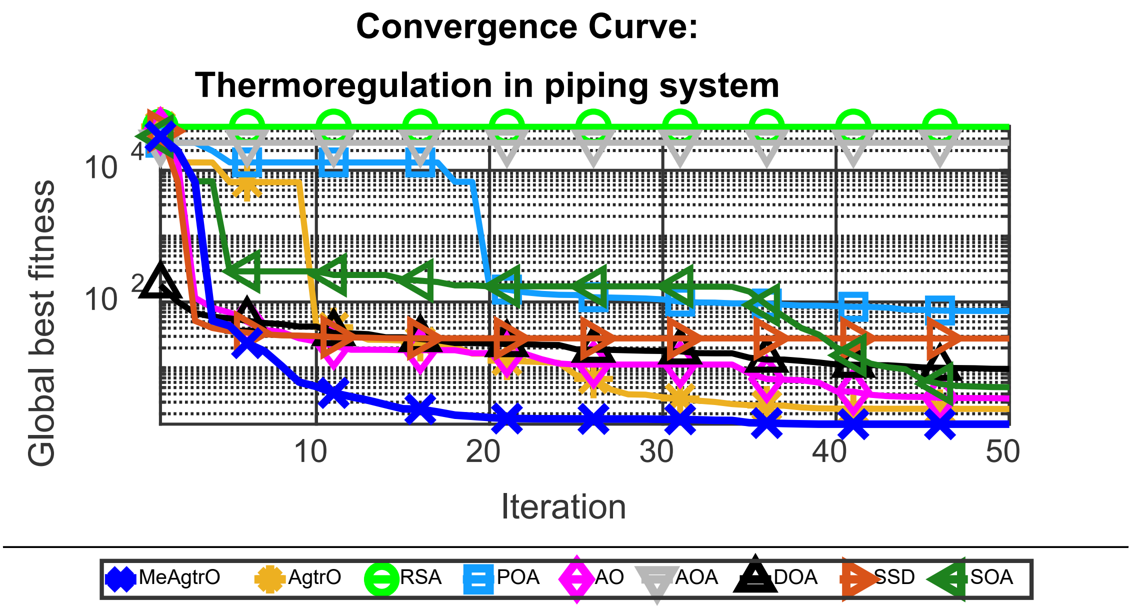

Figure 7. Convergence curves of all algorithms applied to thermoregulation in simulated piping system

It is essential to guarantee that the algorithm has generally adequate clustering properties as a promising swarm-based intelligence. The superiority of the clustering properties convinces the algorithm to a certain extent that it has better local absconding ability, global proximity, and accelerated progress. The clustering properties of the algorithm were evaluated by comparing the position point of an agent with the average position point of the population across the dimension. The degree of alignment of the two plotted linear dimension data determines the superiority of the algorithm in terms of clustering capability. In short, the more aligned the two lines in the cluster plot are, the better the clustering properties of the algorithm, and good clustering indicates the greater the potential of the algorithm to produce higher global optimality in any practical application. For our research application, Figure 8 displays distinguishable clustering plots. Obviously, AgtrO, RSA, POA, AO, AOA and DOA are not even qualified to claim to have good clustering properties. Compared with them, MeAgtrO shows good clustering properties but is still slightly less than perfect. SSD and SOA, on the other hand, provide nearly flawless map alignment of an agent position vector on the mean position vector, revealing that they have superior clustering qualities to MeAgtrO. However, from graphical analysis alone, MeAgtrO is still competitive with SSD and SOA. The satisfactory clustering performance of MeAgtrO can support the claim that MeAgtrO has the strong ability to avoid local optima, which is beneficial for every optimization solution in any domain. Likewise, the fact that MeAgtrO outperforms AgtrO in terms of clustering properties demonstrates the contribution of the proposed variants.

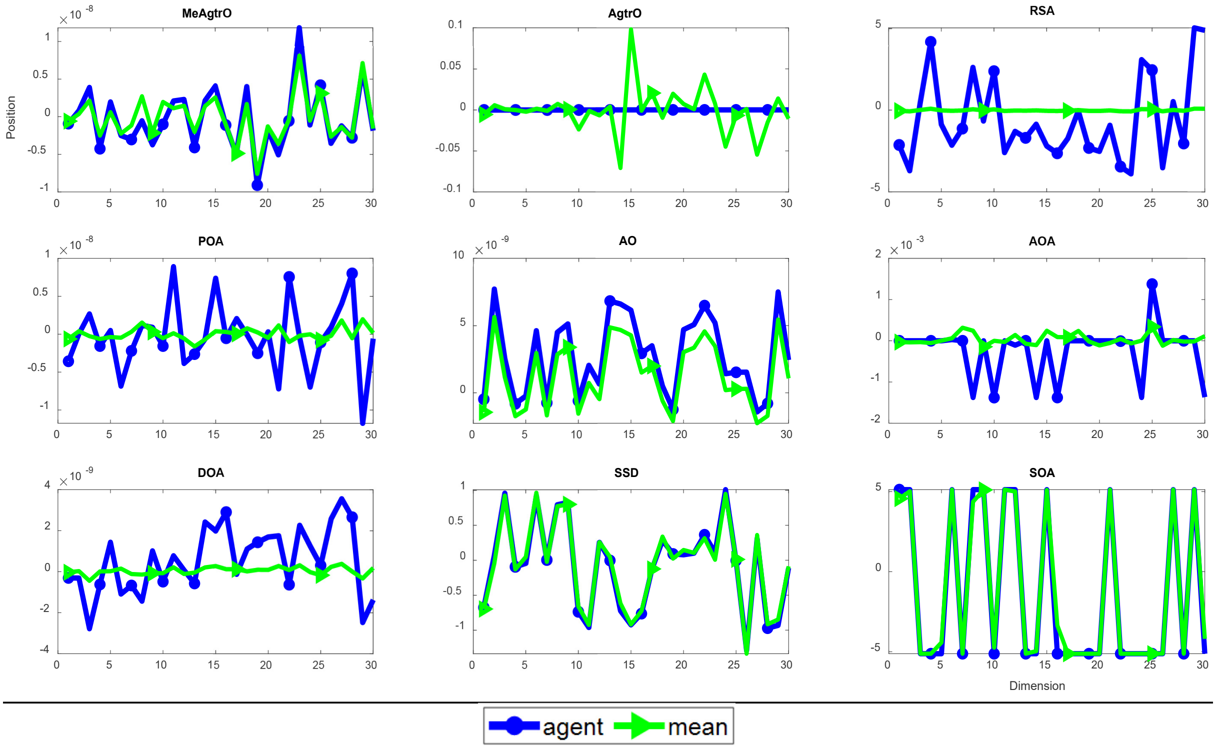

Figure 8. Clustering plots for the selected function in each benchmark set

For deeper validation, step response information obtained by various algorithms applied to thermoregulation were collected and displayed in Figure 9. Note that the set point is 100 oC. Of all the compared algorithms, only MeAgtrO, AgtrO, AO, and DOA could reach the steady state of the set point 100 oC within 10 seconds of simulation time. This shows that only these 4 algorithms show zero steady-state error in the time response. Among them, only MeAgtrO, AgtrO and AO yielded similar rise times of 0.40s, which makes them competitive with each other. However, the settling times contributed by these respective algorithms clearly differentiated their performance: MeAgtrO obtained a settling time of 0.99s, AgtrO obtained a settling time of 1.89s, AO obtained a settling time of 2.96s. Presuming that the overshoot and undershoot from these algorithms do have little affection on the final objective function value, we can hence combine all the evidence and conclude that MeAgtrO yield the best performing step response in this feedback control application. Notably, MeAgtrO provides a solution that can raise the output temperature to the steady set point in the fastest manner with negligible undershoot and overshoot damping, thereby minimizing damage to the heating system. Overall, MeAgtrO has somehow managed to tune the best, most reliable, most efficient, and most robust solutions with superior global best performance and processing efficiency that enable piping systems to achieve the most stable thermoregulation with minimal rise time, settling time, overshoot, and undershoot.

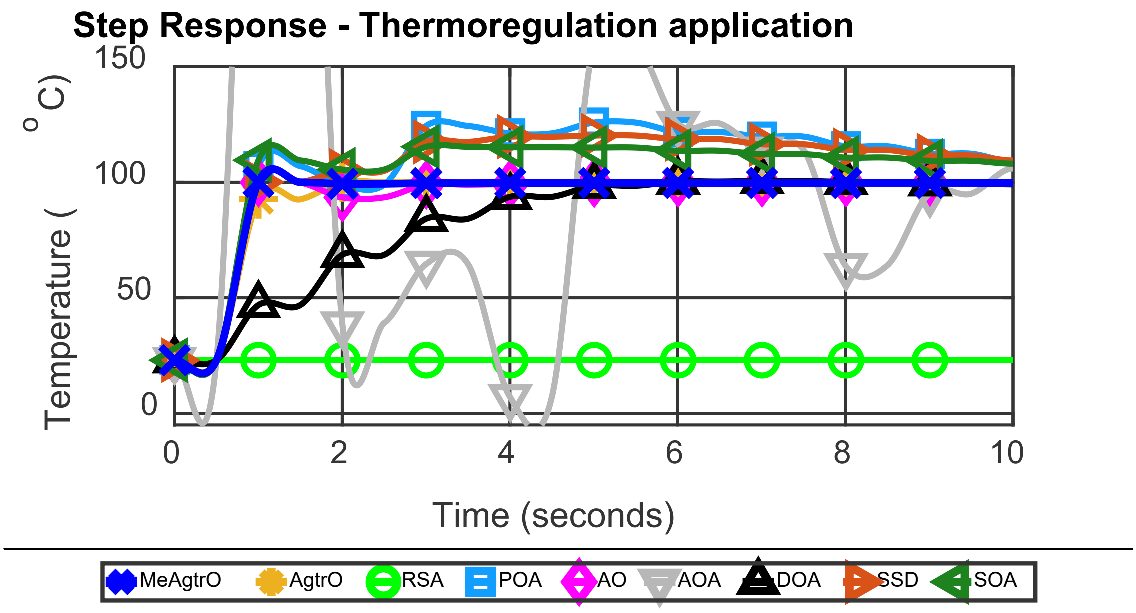

Figure 9. Step response curves of all algorithms applied to thermoregulation in simulated piping system

5. CONCLUSION

In this research work, the proposed MeAgtrO was applied to thermoregulation applications in piping systems, and its performance was compared with eight other comparative algorithms of the same classification. Upon evaluation, MeAgtrO achieved the superior statistical best, mean, and SD results, demonstrating its superior performance in terms of accuracy, reliability, and robustness in its application. MeAgtrO also obtained the best convergence rate and competitive clustering properties, which was supported by statistically plotted convergence curves and clustering maps. In addition, it is demonstrated in the step response diagram that MeAgtrO yielded the least rise time (0.40s), settling time (0.99s), overshoot percentage (0%), and undershoot percentage (0%) with zero steady-state error. All these statements demonstrate that MeAgtrO is successful in every respect as an optimizer. In fact, we can claim that MeAgtrO is highly applicable for industrial control purposes and thus is considered to maintain good performance in a wide range of engineering applications. For any potential upgrades, future emphasis can be on improving processing speed and efficiency according to current application trends.

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