A Micro Dynamic Multi-objective Evolutionary Algorithm for Small-scale Smart Greenhouse with Low-power Microprocessor

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ABSTRACT

Smart greenhouse is a modern agricultural facility that integrates smart control systems to regulate the plant growth environment through advanced intelligent technology and devices. In recent years, smart greenhouses have received widespread attention and have been applied in agriculture. Due to their high energy demands and costs, current smart greenhouses are often impractical for applications with limited resources. Nevertheless, small-scale smart greenhouse with low-power microprocessor, are more suitable for homes, offices, and other fields. Therefore, this paper proposes a micro dynamic multi-objective evolutionary algorithm (**μDMOEA**) for small-scale smart greenhouse with low-power microprocessor, which applies chaotic mapping to select dynamic response strategies based on the fitness of dominant relationships and k-nearest neighbor environmental selection. μDMOEA performs well in the simulation of small-scale smart greenhouses. It not only outperforms SGEA, DNSGA-II, and RVCP in IGD indicator but also plays a good role in adjusting environmental parameters. It demonstrates the feasibility and effectiveness of micro dynamic multi-objective optimization on small-scale smart greenhouse with low-power microprocessor.

CCS CONCEPTS

• **Computer systems organization** → **Embedded and cyber-physical systems**; • **Computing methodologies** → *Modeling and simulation*; • **Theory of computation** → Design and analysis of algorithms.

KEYWORDS

A micro dynamic multi-objective algorithm, Smart greenhouse, Low-power microprocessor

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1 INTRODUCTION

Smart greenhouses have received widespread attention and have been applied in agriculture [13]. However, current smart greenhouses are characterized by high power and cost, which makes them unsuitable for conditions with limited resources. Small-scale smart greenhouses [11] with low-power microprocessor are more suitable for home, office, and other fields. In small-scale smart greenhouses, sensors measure the parameters of the environment, then low-power microprocessors process the data and give instructions to the actuators. Thus, the plant thrives through this process.

Real-world applications such as small-scale smart greenhouses can be modeled as multi-objective optimization problems (MOPs). Specifically, the type of MOPs [12] with the objective function, constraints, and other environmental parameters change over time can be defined as dynamic multi-objective optimization problems (DMOPs). However, normal-sized dynamic multi-objective evolutionary algorithms (DMOEAs) [8] make it difficult to store relevant information and may interrupt program operation midway due to exceeding memory. In this respect, micro multi-objective evolutionary algorithms (μMOEAs) [9] can solve the problems of normal-sized multi-objective evolutionary algorithms (MOEAs) in a simple

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and computationally efficient way on low-power microprocessors [7]. For the above issues, this paper designs a micro dynamic multi-objective evolutionary algorithm (μDMOEA) and applies it to the simulation of small-scale smart greenhouse optimization. The main contributions of this paper can be summarized as follows.

- By analyzing the characteristics of low-power microprocessors and combining the properties of DMOEAs and μMOEAs, this paper suggested the feasibility of applying micro dynamic multi-objective optimization to small-scale smart greenhouses.
- This paper proposes a micro dynamic multi-objective evolutionary algorithm (μDMOEA) based on chaotic mapping dynamic strategy selection.
- The simulation results of μDMOEA in small-scale smart greenhouse demonstrate that the algorithm has good performance in this problem.

This paper is organized as follows. In Section 2, the preliminaries for the research directions of this paper are introduced. Section 3 provides a detailed description of μDMOEA. Section 4 shows the simulation results. Section 5 is the summary of this paper.

2 PRELIMINARIES

2.1 Low-power Microprocessor

Low-power microprocessor is a type of micro computational processing unit designed to solve computing tasks that consume as little energy as possible. With the continuous advancement of electronic technology, low-power microprocessors with stronger performance, smaller size, and lower cost are constantly being produced. Low-power microprocessors possess characteristics such as low power consumption and easy scalability, rendering them an ideal choice for IoT devices in various fields, including smart homes [5], smart agriculture [15], and so on. Meanwhile, their low price, approximately \$5, provides room for their application in a wider field. To achieve excellent low-power microprocessors, low-power processing technology and the selection of device feature sizes play an important role.

2.2 Small-scale Smart Greenhouse

In recent years, the convergence of technology and agriculture has stimulated innovative applications aimed at optimizing crop cultivation and environmental sustainability. Among these advancements, small-scale smart greenhouses [11] have the potential to serve as focal points for algorithmic research and automation systems, enhancing agricultural productivity and resource efficiency.

The mathematical model for the dynamic multi-objective optimization problem of the small-scale smart greenhouse applied in this paper is referenced from [14, 17]. Our work applies the mathematical model of the small-scale smart greenhouse mentioned above to simulation. Based on this real-world problem, this paper uses many hardware devices, such as low-power microprocessors, sensors, etc. The low-power microprocessors that have been programmed with algorithms will optimize the greenhouse environment by analyzing environmental parameters and controlling the actuators. The entire process demonstrates the excellent performance of the micro dynamic multi-objective evolutionary algorithm in small-scale smart greenhouses with low-power microprocessor.

2.3 Micro Multi-objective Evolutionary Algorithm

Micro multi-objective evolutionary algorithms (μMOEAs) are efficient, as they consume low computational resources. μMOEAs search the solution space with a micro population to achieve rapid convergence. Consequently, the population will converge prematurely, leading to a deficiency in diversity. Addressing this issue is a significant challenge for researchers. Over the years, although μMOEAs have not been a popular field, there has still been some related work. Coello and Pulido et al., pioneers in μMOEAs, proposed micro-GA [1], which provided many basic theoretical support. Thereafter, Tiwari et al. introduced typical diversity strategies into μMOEAs to design AMGA [10]. Peng et al. applied μMOEAs to the microgrid energy optimization problem and the proposed μMMABC [9]. Moreover, Peng et al. first introduced decomposition ideas into μMOEAs and developed μMOEAs [7].

In fact, the environment of many real-world problems will change over time. Among these dynamic real-world problems, some problems that normal-sized DMOEAs cannot solve easily. For example, low-power microprocessors with limited computational resources may terminate programs due to insufficient memory during the process. In this case, there is a demand for algorithms [16] that consume low computational resources. Therefore, this paper proposes a micro dynamic multi-objective evolutionary algorithm (μDMOEA).

3 THE PROPOSED μDMOEA

Algorithm 1 μDMOEA

Input: Population size N, ratio of change response solutions ζ
Output: Population Pop

Randomly initialize population Pop ;
while $FEs < MaxFEs$ **do**
  if Environmental change detected **then**
    $selected \leftarrow \{i_1, i_2, ..., i_{\lfloor \zeta * N \rfloor}\}$, i is randomly selected from $\{1, 2, ..., N\}$;
    Generate $Ch = \{ch_1, ch_2, ..., ch_{\lfloor \zeta * N \rfloor}\}$ by using $Eq.(1)$;
    if $mean(Ch) > \zeta$ **then**
      $Pop' \leftarrow Pop(selected)$ using nominal convergence operator ;
      $Pop(selected) = Pop'$;
    else
      $Pop'' \leftarrow Apply\ Eq.(2)\ to\ Pop$;
      $Pop(selected) \leftarrow EnvironmentalSelection(Pop'')$; // $Ref.\ to\ SPEA2$ [19]
    end if
  else
    $Off \leftarrow recombination(Pop)$;
    $Pop \leftarrow EnvironmentalSelection(Pop \cup Off)$;
  end if
end while

Table 1: Mean and standard deviation IGD of comparison with SGAE, DNSGA-II, RVCP on real-world problem SSG (small-scale smart greenhouse problem).

Problem	M	D	SGEA	DNSGA-II	RVCP	μDMOEA
SSG	2	6	1.0673e-1 (9.99e-3) -	1.2133e-1 (1.34e-2) -	1.0615e-1 (1.23e-2) -	**9.5554e-2 (7.77e-3)**
+/-/=			0/1/0	0/1/0	0/1/0	—
Rank			3.00	4.00	2.00	**1.00**

The main idea of μDMOEA is to select response strategies for dynamic changes within the environment through chaotic mapping [9], and optimize the population based on different approaches. When comparing the value of chaotic numbers with the ratio of change response solutions, the approach enables the population to reach nominal convergence, or respond to changes based on Gaussian perturbation and truncation on the population. The method of environmental selection is the diversity maintenance strategy used in SPEA2 [19].

Algorithm 1 presents the pseudocode for μDMOEA, where the inputs consist of the population size and the ratio of change response solutions. The first step is to randomly initialize and generate an initial population of size N. With the implementation of dynamic and static response mechanisms, the algorithm outputs an optimized population.

In the process of static optimization, the parent population undergoes recombination to generate offspring, and the combined population is subsequently subjected to environmental selection, which updates the population through truncation. The environmental selection strategy refers to SPEA2 [19], which calculates fitness based on dominance relationships and k-nearest neighbor selection.

$$x_{k+1} = x_k + \alpha x_k \left(1 - \alpha\right) \tag{1}$$

where x_k, x_{k+1} are the chaotic numbers, k is the index of individuals. α is a parameter that regulates chaotic mapping.

When environmental changes are detected, μDMOEA selects a ratio of change response solutions from the population and calculates their chaotic mapping values using equation (1). If the average value of the chaotic map is greater than the ratio of environmental response solutions, then the nominal convergence operator is used to update the response individuals. The concept of nominal convergence was proposed in [1], which is a method in μMOEAs that can effectively improve convergence.

$$\begin{cases} x_i' = x_i + N(\mu, \sigma^2), & if\ rand(0,1) < 1/D \\ x_i' = x_i, & otherwise \end{cases} \tag{2}$$

where x and x' are solutions before and after Gaussian perturbation, respectively. D is the number of decision variables.

If not, μDMOEA uses an environmental selection strategy that is familiar with the static optimization process. This involves selected change response solutions from the population after applying equation (2) (Gaussian perturbation [3, 6]), which helps compensate for population diversity. Repeat the above process until the termination conditions are met to terminate μDMOEA.

4 SIMULATION

4.1 Simulation Setting

- Population size: The population size in comparison algorithms and real-world problems is set to 100.
- Maximum number of function evaluations ($MaxFE$): The value of $MaxFE$ in the simulation is set to 10000.
- Problem: the real-world problem SSG (small-scale smart greenhouse problem) in Section 2.2.

4.2 Simulation Results and Analysis

This paper focuses on the simulation of the small-scale smart greenhouse. As shown in Figure 1, the simulation structure mainly includes electronic components (microprocessors, sensors, actuators, etc.), the greenhouse environment, and the cloud platform. Sensors measure environmental parameters such as humidity and temperature, and send data to the MPU. After receiving the data from sensors, the MPU will perform computational analysis and process the response to find a suitable solution on the PF for feedback. The feedback will be sent to the actuators, which will regulate the environment to enable the plants in the greenhouse to thrive. The data recorded during the above process will be uploaded to the IoT platform based on Alibaba Cloud. The platform can record simulation data in real-time, providing users with more convenient data recording and more efficient monitoring feedback.

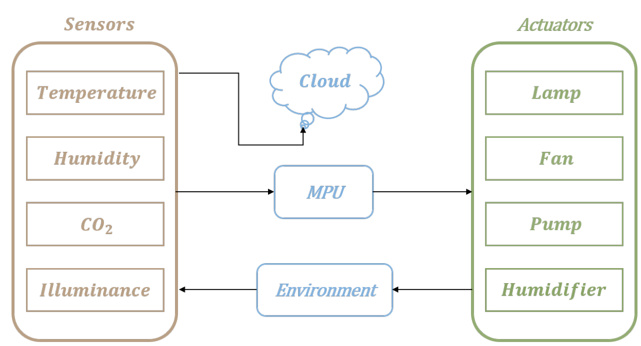
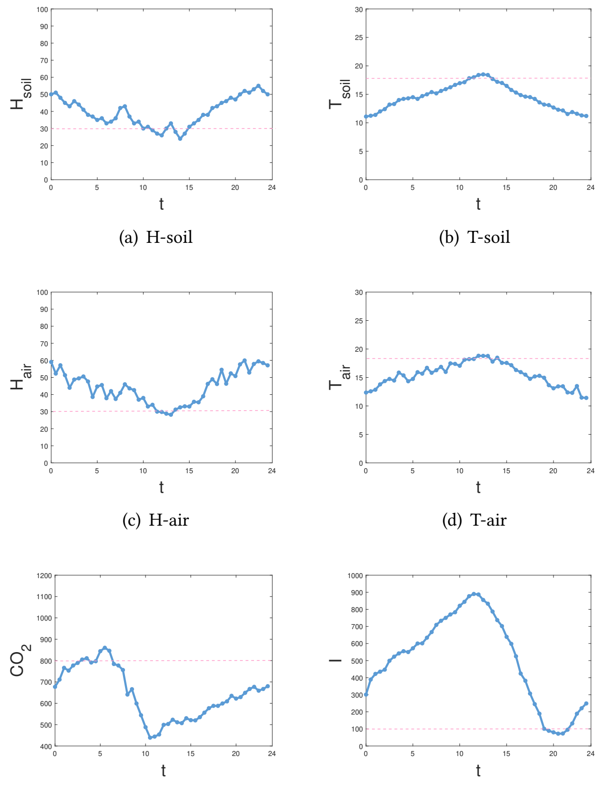


Figure 1: The control structure of small-scale smart greenhouse.

To verify the effectiveness of μDMOEA in small-scale smart greenhouses with microprocessor, three dynamic multiobjective evolutionary algorithms are compared, including typical dynamic multi-objective evolutionary algorithms SGEA [4], DNSGA-II [2], and advanced RVCP [18]. The experimental results are shown in



(a) H-soil (b) T-soil

(c) H-air (d) T-air

(e) CO2 (f) I

Figure 2: Trend curves of environmental parameters within 24 hours (red line = threshold).

Table 1. The IGD value of μDMOEA is smaller than the other three algorithms and ranks higher, indicating that μDMOEA performs better in the small-scale smart greenhouse.

Furthermore, Figure 2 presents the continuous regulatory performance of the μDMOEA over 24-hour in the small-scale smart greenhouse with microprocessor. This paper sets thresholds for different environmental parameters, and when the environmental parameter values are above/below the threshold, it indicates that they exceed the values required for a normal growth environment. When the small-scale smart greenhouse environment changes, μDMOEA processes the data received from sensors and provides feedback to the actuators. This dynamic process ensures that the plants within the small-scale smart greenhouse can maintain healthy growth.

The above simulation results not only demonstrate the excellent performance of μDMOEA on small-scale smart greenhouse, but also demonstrate the feasibility of micro dynamic multi-objective evolutionary optimization in it.

5 CONCLUSION

This paper has suggested a micro dynamic multi-objective evolutionary algorithm (μDMOEA) based on chaotic mapping dynamic strategy selection. In the simulation, μDMOEA was compared with three DMOEAs and programmed into low-power microprocessors for small-scale smart greenhouse problems. The results indicate that it has a good feasibility of applying micro dynamic multi-objective evolutionary algorithms in a small-scale smart greenhouses with microprocessor.

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