Furnace Temperature Curve Model Based on Particle Swarm Optimization

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Abstract. In this paper, based on the process parameter distribution of industrial automation equipment, an optimization control model is proposed, which adopts advanced numerical methods to adjust the parameters, and introduces the particle swarm optimization algorithm to finely control the process parameters in multiple regions. Experimental results show that the optimization algorithm can effectively improve the accuracy of equipment parameter adjustment, so as to ensure the stability of production process and product quality. This method is not only applicable to traditional industrial automation control systems, but also plays an important role in the field of intelligent manufacturing. Future research can further expand the model to adapt to more complex industrial scenarios, and provide theoretical basis and technical support for the formulation of multi-dimensional control strategies.

Keywords: Particle swarm optimization algorithm, industrial automation, optimization control.

1. Introduction

With the rapid development of industrial automation technology, the precise control of the production process has gradually become a key factor to improve production efficiency and product quality. Especially in the complex production environment, how to effectively realize the coordinated control of multiple regions and parameters has become an urgent problem to be solved in the modern manufacturing industry. In processes such as reflow soldering, heat treatment, etc., changes in process parameters directly affect the quality of the product and the stability of production. Accurate process parameter control can improve the efficiency and reliability of the production line while ensuring product performance, so as to achieve the purpose of energy saving, consumption reduction and cost reduction. Therefore, how to effectively control and optimize multiple process parameters in the production process has become an important research direction in the field of industrial automation control.

In today's industrial production, traditional temperature control methods usually use a single interval setting or experience-based adjustment, which can meet basic production needs in some cases, but often cannot cope with complex fluctuations in process parameters in the production process. For example, in the reflow soldering process, the temperature control of each zone is often carried out independently, ignoring the interaction between regions, resulting in large temperature differences between different zones, which in turn affects the welding quality and production stability. Therefore, how to optimize the control of multi-zone process parameters in complex industrial environments has become one of the bottlenecks of current technology development.

At present, many scholars have conducted a lot of research on temperature control issues. Traditional temperature control models mostly rely on the classical heat conduction equation, combined with sensors and feedback control algorithms for real-time adjustment. For example, some studies have simulated the heat transfer process through a one-dimensional heat conduction equation and precisely adjusted the temperature based on a PID control algorithm. However, most of these studies focus on the control of a single temperature range or local region, and fail to effectively solve the interaction between multiple regions and the optimization of multi-dimensional process parameters [1]. In addition, with the increasing complexity of the production process, the existing control methods often face the contradiction between local optimization and global optimization, and it is difficult to realize the comprehensive optimization of the entire production process.

At the same time, the particle swarm optimization algorithm (PSO), as a swarm intelligence optimization algorithm, has shown good performance in multi-objective optimization problems. In recent years, the application of PSO algorithm in industrial control systems has gradually increased, mainly focusing on parameter adjustment and system optimization. Many studies have tried to apply PSO algorithms to temperature control, equipment scheduling, energy management and other fields, and have achieved certain results. However, most of the existing studies are limited to the optimization of a single target or simple linear systems, and there is still a lack of in-depth discussion on complex multi-region automation control systems, especially in the collaborative optimization of multi-region parameters.

In order to solve the above problems, this paper proposes a new optimization model for industrial automation process parameters based on one-dimensional heat conduction equation. By introducing the particle swarm optimization algorithm to fine-tune the multi-region process parameters, we realize the global optimization of multi-dimensional control parameters and solve the problem of poor coordination of multi-region process parameters in the traditional method. The main contributions of this paper are:

In this paper, a parameter distribution model of industrial automation process based on heat conduction equation is proposed, and the particle swarm optimization algorithm is combined to optimize multiple parameters. This model is applied for the first time to the fine control of multi-region process parameters, which solves the global optimization problem that is difficult to achieve by traditional control methods.

The finite difference method is used to discretize the heat conduction equation numerically, so that the continuous control process is transformed into a discrete system, and numerical simulation and optimization are carried out. This method can effectively deal with dynamic changes in complex production environments, and provides theoretical support for industrial automation.

The effectiveness of the model is verified by comparative experiments, and the results show that the method can significantly improve the control accuracy of the production process, ensure the product quality, and improve the stability and efficiency of the production line.

The structure of this paper is as follows: Chapter 2 introduces the relevant theories, including the basic principles of the one-dimensional heat conduction equation, the basic concepts of the particle swarm optimization algorithm, and the application of the finite difference method. Chapter 3 describes the experimental design and model building process in detail, focusing on how to model and optimize industrial automation processes through numerical discretization and optimization algorithms. Chapter 4 presents the experimental results and compares them with traditional methods to analyze the application effect of the optimization model in the production process. Finally, Chapter 5 summarizes the research results of this paper and proposes future research directions.

2. Related Theory

2.1. One-dimensional heat conduction equation

The one-dimensional heat conduction equation is used to describe the temperature change of an object in a certain dimension. The model in this paper assumes that the heat conduction in the furnace propagates in one direction and that the thermal diffusivity is constant. The basic equation is:

$$\frac{\partial T(x,t)}{\partial t} = \alpha \frac{\partial^2 T(x,t)}{\partial t^2} \tag{1}$$

Where $T(x,t)$ represents the temperature at time t at position x; α is the thermal diffusivity (also known as thermal conductivity), which is defined as $\alpha = \frac{k}{\rho c_p}$, where k is the thermal conductivity, ρ is the density of the material, and c_p is the specific heat capacity; $\frac{\partial T}{\partial t}$ indicates the rate of change of temperature over time; $\frac{\partial^2 T}{\partial t^2}$ represents the second derivative of temperature with space, reflecting the distribution of temperature in space.

The equation shows that the rate of temperature change at a certain point is related to the spatial distribution of temperature near that point, and the temperature always spreads from a higher temperature region to a lower temperature region.

2.2. Particle swarm optimization algorithm

The particle swarm optimization algorithm is a swarm intelligence-based optimization algorithm inspired by the group behavior of birds or fish in nature, especially their coordinated actions when searching for food [2, 3]. PSO optimizes problem solving by simulating the exchange of information between individuals in a population. Each individual is called a "particle" and is represented in the solution space as a potential solution. Particles adjust their position and velocity by tracking the historical best position they have found (individual best position) and the current optimal solution in the entire population (global best position) to gradually approach the optimal solution of the problem. Through this dynamic adjustment process, the particle swarm optimization algorithm can effectively find the optimal solution or approximate optimal solution in complex multivariate problems.

The advantages of particle swarm optimization algorithm are that it has fast convergence speed, is easy to implement, and is suitable for dealing with complex multi-objective optimization problems. In this paper, through multiple iterations, the particle swarm optimization algorithm can accurately adjust the parameters of each temperature zone, so that the welding speed and temperature setting of the conveyor belt can operate in the optimal range, so as to ensure the overall consistency of the temperature profile. Through such optimization, the process stability of reflow soldering is effectively improved, the welding quality is significantly improved, and the optimized temperature profile can better cope with the process requirements in actual production.

2.3. Finite difference method

The finite difference method is a commonly used numerical calculation method [4], which is mainly used to solve the problem of partial differential equations and ordinary differential equations. The basic idea is to transform an otherwise continuous differential problem into a discrete system of algebraic equations by replacing a continuous region with a finite number of discrete points. In this method, the continuous variables of time or space are discretized, and the differential operations in the original equation are replaced by numerical approximate differential operators, so as to obtain an approximate solution to the original problem.

In the finite difference method, the solution area is usually divided into a regular grid, with each node of the mesh representing a discrete point. Each differential term of a differential equation, such as a first or second derivative, can be approximated by the difference between adjacent points. It is shown in Figure 1:

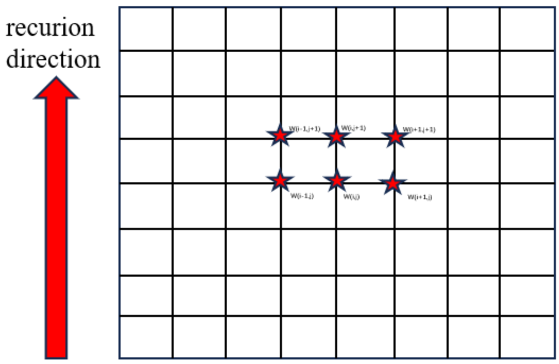

Figure 1. Schematic diagram of the finite difference method to solve the equation

3. Experimental Design

The main purpose of this experiment is to improve the control accuracy and stability of multi-region process parameters by establishing a process parameter model of industrial automation equipment, numerical simulation and optimization. The whole experimental process includes the establishment of the model, the numerical discretization and the optimization of the parameters, and the heat conduction equation and the particle swarm optimization algorithm are combined in the experimental design to carry out the fine control of multi-region parameters.

The overall process of the experiment is as follows: firstly, the process parameter model of industrial automation equipment is established based on the one-dimensional conduction equation, and the finite difference method is used to discretize the model numerically to obtain the discrete process parameter distribution. Then, the particle swarm optimization algorithm (PSO) was used to optimize the key process parameters in the discrete model to find the optimal solution that could meet the process requirements, so as to realize the collaborative optimization control of multi-region parameters.

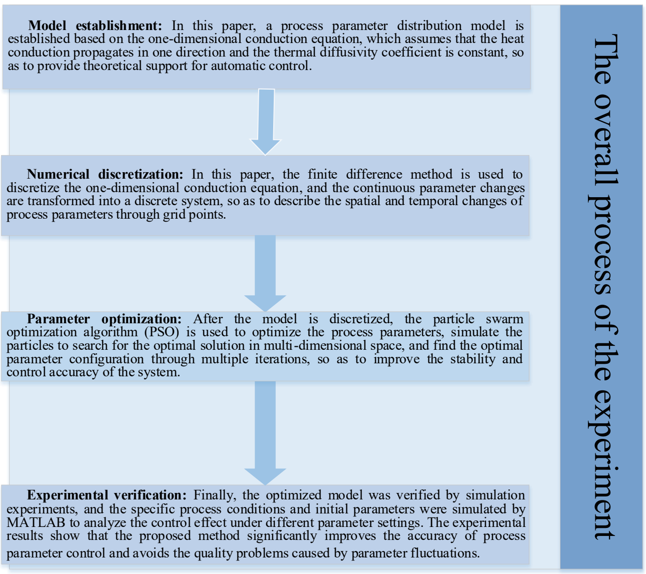

Figure 2. Experimental Flow Chart

3.1. Establishment of model

In order to achieve accurate control of each temperature zone of the reflow oven, a temperature distribution model based on the one-dimensional heat conduction equation is established to simulate the temperature change process in the reflow furnace [5].

1) Model assumptions and basic equations

In reflow ovens, the temperature control of the different temperature zones directly affects the quality and reliability of welding. In this paper, the spatial and temporal variations of temperature in the reflow furnace are described based on a one-dimensional heat conduction equation. The model assumes that heat is conducted in only one direction in the reflow oven and that the thermal diffusivity remains constant. This assumption applies to the heating area within the reflow oven, ensuring the simplicity and computability of the model The heat conduction equation is used to describe the change in temperature over time and space, and its mathematical form is as follows [6]:

$$\frac{\partial u(x,t)}{\partial t} = A\frac{\partial^2 u(x,t)}{\partial t^2} \tag{2}$$

Where $T(x,t)$ represents the temperature at time t at position x; α is the thermal diffusivity, which reflects the ability to conduct heat.

2) Boundary conditions and initial conditions are set

In order to solve the heat conduction equation, boundary conditions and initial conditions need to be set. In the reflow oven model, the boundary conditions assume that the temperature at the furnace boundary remains constant to represent a stable input to the furnace heat source.

If the room temperature is a°C, the initial conditions are:

$$f(h,0)=a°C(0\le h\le L) \tag{3}$$

L is the thickness of the component.

Find the boundary conditions of the contact surface between the welding area and the air in the furnace, according to Newton's cooling law:

$$-k_i\frac{\partial f(h_1,t)}{\partial h}=h_i(u(x,t)-f(h_1,t)) \tag{4}$$

The welding area is symmetrical with the welding center as the symmetry point [7], if h_1 is the head end and h_m is the tail end, then:

$$\mathrm{k}_i\frac{\partial f(h_m,t)}{\partial h}=h_1(u(x,t)-f(h_m,t)) \tag{5}$$

The equations solved by each equation of the model are combined to obtain the system of equations for the welding region:

$$\begin{cases}\dfrac{\partial u(h,t)}{\partial t}=B\dfrac{\partial^2(h,t)}{\partial h^2}\\ f(h,0)=25(0\le h\le L)\\ -k_i\dfrac{\partial f(h_1,t)}{\partial h}=h_i(u(x,t)-f(h_1,t))\\ k_i\dfrac{\partial f(h_m,t)}{\partial h}=h_i(u(x,t)-f(h_m,t))\end{cases} \tag{6}$$

3.2. Numerical discrete solution

Since the heat conduction equation is a partial differential equation, it is difficult to solve it directly. Therefore, in this paper, the finite difference method is used to discretize the heat conduction equation [8], and the continuous problem is transformed into a discrete problem for numerical solution [9] Differential in time and space, Δx , Δt is the step size, and the temperature is transferred:

$$\begin{cases}\dfrac{\partial f(h,t)}{\partial t}=\dfrac{f(h,t_i)-f(h,t_{i-1})}{\Delta t}\\ \dfrac{\partial^2 f(h,t)}{\partial h^2}=\dfrac{f(h_{i+1},t)+f(h_{i-1},t)-2f(h_i,t)}{(\Delta h)^2}\end{cases} \tag{7}$$

Bringing in Equation $\frac{\partial f(h,t)}{\partial t}=B\frac{\partial^2 f(h,t)}{\partial h^2}$ yield $\frac{f(h,t_i)-f(h,t_{i-1})}{\Delta t}=B\frac{f(h_{i+1},t)+f(h_{i-1},t)-2f(h_i,t)}{(\Delta h)^2}$ the two boundaries are discussed, and the two boundaries are inversely symmetrical:

$$\begin{cases}\dfrac{f(h_m,t)-f(h_{m-1},t)}{\Delta h}=h_i(u(x_m)-f(h_m,t))\\ \dfrac{f(h_1,t)-f(h2,t)}{\Delta h}=h_i(u(x_1)-f(h_1,t))\end{cases} \tag{8}$$

The solution process is transformed into a matrix solution, and the following results are:

$$\begin{bmatrix} \frac{1}{\Delta h}+h_i & -\frac{1}{\Delta h} & 0 & 0 & 0 & \cdots & \cdots & 0 \\ \frac{B}{\Delta h^2} & -(\frac{2B}{\Delta h^2}+\frac{1}{\Delta t}) & \frac{B}{\Delta h^2} & 0 & 0 & \cdots & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & -\frac{1}{\Delta h} & \frac{1}{\Delta h}+h_i \end{bmatrix} \cdot \begin{bmatrix} f(h_1,t_1) \\ f(h_2,t_1) \\ \vdots \\ f(h_m,t_1) \end{bmatrix} = \begin{bmatrix} h_i \mathrm{u}(x_1) \\ -\frac{f(h_2,t_0)}{\Delta t} \\ \vdots \\ h_i u(x_m) \end{bmatrix} \tag{9}$$

After establishing the temperature distribution model, the particle swarm optimization algorithm (PSO) is introduced to optimize the process parameters in each temperature zone of the reflow furnace. PSO is an optimization algorithm based on swarm intelligence, which can effectively deal with the global optimization problem of multi-region parameters. Each particle represents a set of possible configurations of temperature zone parameters, and by constantly updating their positions (i.e., temperature setpoints), the optimal solution is found to make the entire temperature profile smoothest and meet the needs of the process.

Through the optimization of PSO, the model can significantly improve the welding quality while ensuring the stability of temperature control, ensuring that each process link can reach the best temperature state.

3.3. Experimental verification

The optimized model was analyzed in detail by using simulation experiments with specific process conditions and initial parameters. MATLAB tools were used to simulate the control effect under different parameter settings, and the effectiveness of the particle swarm optimization algorithm on the optimization of process parameters was verified. The experimental results show that the optimized model has significant improvements in temperature uniformity, control accuracy, and production line stability, especially in coping with multi-region parameter fluctuations and maintaining process consistency. After the above experiments and analysis, a series of conclusions are drawn, including: the optimization model can significantly improve the control accuracy of process parameters, reduce the occurrence of product quality problems, and effectively improve the stability and automation control level of the system.

1) Simulation results of temperature profiles

The interstitial temperature between different temperature zones can be expressed by a linear equation as:

$$u(x) = ax + b \tag{10}$$

Bringing in the temperature of each temperature zone, the temperature distribution curve of the reflow furnace is calculated:

Table 1. Reflow oven temperature distribution curve

x	Temperature zone	Temperature (℃)
[0, 25]	**Furnace front area**	$\frac{t_c-0.25}{0-0.25}*25+\frac{t_c-0}{0.25-0}*175$
[25, 197.5]	**Low temperature zone1-5**	175
[197.5, 202.5]	**Gap 5**	$\frac{t_c-2.025}{1.975-2.025}*175+\frac{t_c-1.975}{2.025-1.975}*195$
[202.5, 233]	**Low temperature zone 6**	195
[233, 238]	**Gap 6**	$\frac{t_c-2.38}{2.33-2.38}*195+\frac{t_c-2.33}{2.38-2.33}*235$
[238, 268.5]	**Low temperature zone 7**	235
[268.5, 273.5]	**Gap 7**	$\frac{t_c-2.735}{2.685-2.735}*235+\frac{t_c-2.685}{2.735-2.685}*255$
[273.5, 339.5]	**Low temperature zone 8-9**	255
[339.5, 344.5]	**Gap 9**	$\frac{t_c-3.445}{3.395-3.445}*235+\frac{t_c-3.395}{3.445-3.395}*25$
[344.5, 435.5]	**Area behind the furnace**	25

The temperature profile inside the furnace is programmed by MATLAB [10], as shown in Figure 3:

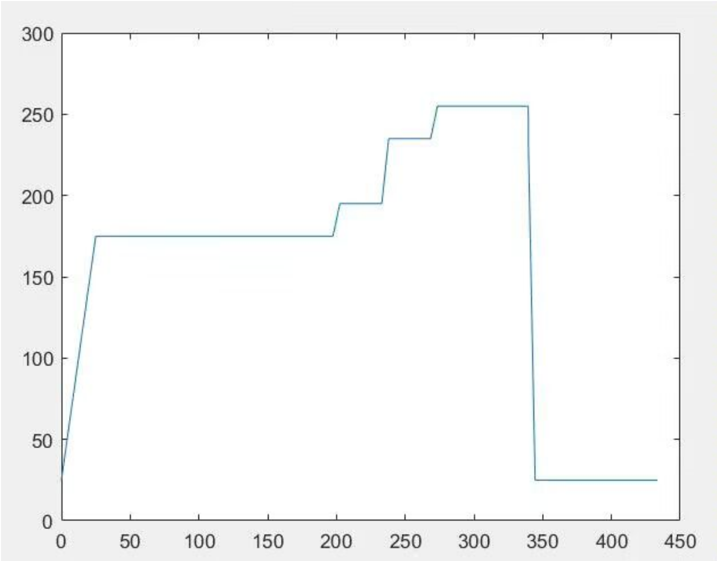

Figure 3. Temperature profile in the furnace

Then, MATLAB was used to simulate the central temperature of the welding area, and the simulation results showed that the central temperature of the welding area was distributed in each temperature zone and gradually changed. The optimized temperature profile can effectively control the temperature rise and fall process, so that the peak temperature and furnace speed in the welding process meet the process requirements.

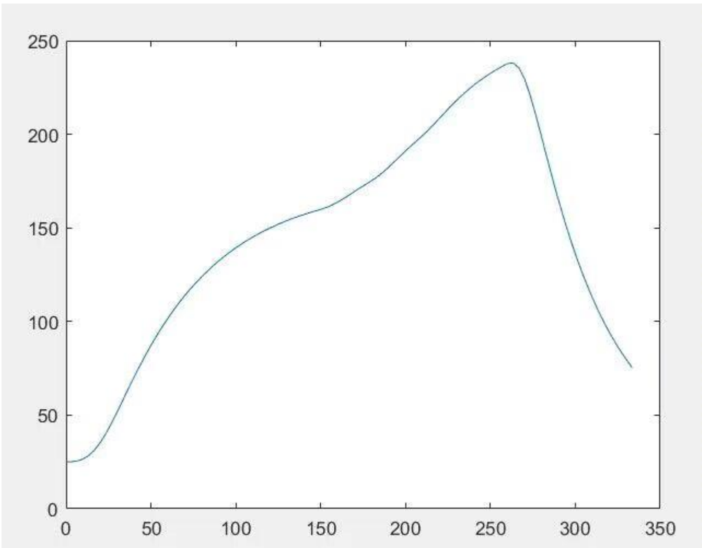

Figure 4. Simulation results of the temperature profile

4. Result And Discussion

Experimental simulation results verify the effectiveness of the proposed optimization model. Through the optimized process parameters, the parameter adjustment of each equipment can be maintained within the optimal range, which significantly improves the control accuracy and product quality in the production process.

Based on the experimental results, the following are the changes in the furnace and inside the components before and after temperature optimization:

Table 2. Experimental result

project	Maximum temperature before optimization (°C)	Optimised maximum temperature (°C)	result
The maximum temperature in the furnace temperature zone	300	280	Temperature drop, smooth control, avoid overheating
The maximum temperature inside the component	270	250	The temperature rises smoothly and is controlled in the optimal range

Furnace temperature: Before optimization, the maximum temperature in the furnace temperature zone was about 300°C, and after optimization, the temperature was reduced to 280°C, showing a step-like upward trend. This change effectively reduces temperature fluctuations in the temperature zone, resulting in a smoother temperature, helping to reduce the risk of overheating and extending the life of the equipment.

Component internal temperature: Before optimization, the internal temperature peak of the component was about 270°C, and after optimization, the peak temperature is controlled at 250°C, and the temperature curve is smoother. This temperature control makes the welding process more stable, helping to improve weld quality and product consistency.

After a series of experimental derivation and simulation analysis, the following results are obtained to verify the effectiveness of the optimization model in process parameter control. Figure 1 shows the temperature setting curve inside the furnace, while Figure 2 shows the temperature change inside the controlled components. These results show that the model has a significant effect in the optimal control of multi-region process parameters.

As can be seen in Figure 4, the temperature curve in the furnace shows a stepwise change in the number of steps, with the set temperature increasing progressively to a maximum of about 280°C. This stepped heating mode facilitates the phased heating of the different temperature zones in the reflow process, ensuring a gradual change in temperature from one temperature zone to meet the different requirements of the welding process.

Figure5 shows that the temperature inside the component gradually rises over time, peaking around 250°C and then beginning to fall. The temperature curve shows a smooth trend, which indicates that under the optimal control, the internal temperature of the component can maintain a stable upward trend in the heating stage, avoiding overheating or uneven temperature, and thus improving the stability of welding quality.

Through the above research and analysis, it can be concluded that the optimization model proposed in this paper can effectively control the temperature change of each temperature zone in the furnace and ensure the stable temperature distribution inside the components, so as to significantly improve the control accuracy of process parameters, effectively reduce the impact of temperature fluctuations on product quality, and provide a reliable solution for the temperature control of industrial automation systems.

5. Conclusion

In this paper, we study the temperature control and optimization problem in the reflow soldering process, establish a temperature distribution model based on the one-dimensional heat conduction equation, and use the particle swarm optimization (PSO) algorithm to achieve accurate control of multi-region parameters. Experimental results show that the model can effectively stabilize the temperature fluctuation, maintain the optimal process conditions in each region, and significantly improve the welding quality and consistency, which verifies the reliability and effectiveness of the proposed model. This method can be generalized to other industrial application scenarios that require accurate thermal management and parameter optimization in multiple regions.

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