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Research on Intelligent Control of a 10-Channel Microwave Input Heating Microwave Oven

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ABSTRACT

The increasing demand for precise temperature control and specialized process control in industrial microwave ovens has led to the exploration of advanced control algorithms. To address these challenges, innovative neural network control algorithms have been introduced. This article delves into the heating mechanism of a 10-channel high-power industrial microwave oven and offers a mathematical explanation for the microwave heating process in the chamber. Through MATLAB simulations, the heating process and the RBF neural network adaptive control system were investigated, demonstrating promising performance. An intelligent control system was then designed, incorporating components such as a 10-channel magnetron, microwave cavity, temperature sensor, and STM-32 microcontroller. Utilizing an RBF neural network adaptive control algorithm, this system independently adjusts 10 microwave inputs to achieve heating and maintain the desired temperature. Subsequently, a 10kW 10-channel high-power industrial microwave oven RBF neural network adaptive control system was implemented and experimentally validated for its effectiveness. This innovative approach offers adaptive intelligent control, enhancing performance across diverse operating conditions.

Keywords: Radial Basis Function (Rbf) Neural Network, Heat Transfer Mechanism, Matlab Simulink, Intelligent Control System, K-Type Thermocouple.

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INTRODUCTION

Microwave heating technology, originating in the 1800s, saw pivotal moments like Percy Spencer's discovery in 1945 and the release of the first microwave oven in 1947. James Clerk Maxwell's equations from 1864 laid the foundation for radar systems. Albert W. Hull's 1925 invention marked early industrial applications. Industrial microwave generators emerged in the 1970s and 1980s with solid-state electronics advancements. Applications diversified into medicine, chemistry, and nanotechnology, fostering new materials and waste treatment methods. Industrial microwave ovens, with multi-megawatt capabilities, revolutionized large-scale heating. Ongoing innovations target higher power

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efficiency and novel materials for diverse applications, ensuring microwave heating technology's continued relevance and impact on modern industries.

Microwave heating technology has witnessed continuous advancements since the conclusion of World War II. Unlike conventional heating methods relying on heat conduction, microwave energy offers a distinct approach to heating various materials efficiently [1]-[4]. Over the past 77 years, microwaves have found applications in diverse fields, categorized into low, medium, and high-temperature treatments [5], [6], [7], [8]. Low-temperature treatments encompass food, wood, textiles, and rubber processing, while medium-temperature treatments involve carbon nanotube synthesis, glass melting, and metal and ceramic sintering. High-temperature treatments exceeding 1000°C, cater to specialized applications. In recent years, the utilization of microwave heating has surged across food preparation and advanced material processing domains. Notably, the industrial sector has witnessed a surge in microwave heating equipment adoption due to its high-power demand. Professors Yang Biao and Peng Jinhui from Kunming University of Science and Technology pioneered a selenium-rich slag deep drying system integrating microwave sources [9]. This system, operating at 2.45GHz with adjustable power up to 54KW, significantly enhances drying efficiency by aligning heat conduction and water diffusion directions, resulting in rapid dehydration with less than 1% residual moisture content. Further research at Chongqing University and Kunming University of Science and Technology delves into temperature regulation during microwave heating processes. Globally, institutions like Oak Ridge National Laboratory (USA), as well as those in Japan, Korea, France, Poland, and India, actively contribute to microwave heating research [2], [4], [10], [11]. Despite advancements, challenges persist, such as the non-uniform heating characteristic of microwave ovens, prompting manufacturers to explore methods to enhance heating uniformity [12], [13], [14]. Recent investigations focus on altering food composition and geometry and exploring hybrid heating techniques integrating hot air, infrared, and microwave radiation [15], [16], [17].

Additionally, researchers explore the impact of stirrers and varied frequencies on heating uniformity, leveraging advancements in microwave oven production and reaction vessel technologies [18]. Temperature control in microwave heating has advanced from open-loop to switch, neural network, and improved control methods. In microwave systems, managing microwave power and external ambient temperature are pivotal, with power size being paramount. Lambert's law estimates power distribution in practical scenarios like heating, thawing, and drying substances. However, complexities in reaction cavities often render power distribution insoluble, leading to uncertain process parameters. Bang-Bang control simplifies closed-loop temperature control, as seen in microwave-dried apple slices. Systems like microwave-assisted pulse vacuum drying incorporate Bang-Bang control. Carrot drying employs Bang-Bang, linear, and 3-step temperature control methods. While NN control offers robustness, data-driven control strategies gain traction for addressing drawbacks. [19], [20], [21]

Research Objective

The research focuses on analyzing the control strategy of multi-feed microwave heating equipment and its impact on heating uniformity, temperature rise characteristics, and thermal runaway suppression. It explores both mechanism-model-based and data-based control strategies, with artificial neural networks (ANN) particularly suited for complex multi-feed heating processes. Conventional PID control in multi-input systems often lacks precision, necessitating a deeper understanding. The investigation formulates mechanistic models for microwave heating processes, progressing from simple to complex scenarios. Intelligent algorithms refine model parameters for precise control. The study aims to develop an intelligent control method for a 10-channel microwave system, enabling autonomous heating control across various sample temperatures. The control system, utilizing the STM32 microcontroller, NNC

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method, MATLAB Simulink, and Keil Uvision5 IDE, regulates temperature and energy consumption and is tested under diverse load conditions and environmental temperatures for efficiency assessment.

LITERATURE REVIEW

There are several industrial uses for electromagnetic radiation, including gamma rays, x-rays, ultraviolet rays, infrared rays, and radio waves [28]. Microwaves, which are a component of the spectrum of electromagnetic fields, have a frequency range of 0.3 (300 MHz) to 300 GHz and are found between the infrared region and regular radio waves. This frequency range is equivalent to wavelengths between 1 m and 1 mm (0.001 m). Microwave wavelengths of 915 MHz, infrared (896 MHz in the UK), and 2.45 (+/-0.05) GHz, which correspond to 32.8 cm and 12.2 cm in free space, respectively, are of special relevance for microwave heating. Both of these frequencies are employed in industrial systems since they have been designated for industrial, scientific, and medical (ISM) use in the majority of nations [25], [26].

Microwave processing offers a unique and efficient energy source for various thermal applications, such as drying, sterilization, and ceramic sintering [26]. Despite its rapid and straightforward heating capabilities, microwave heating is notably non-uniform [27]. However, it still presents numerous advantages over traditional heating methods. Microwave heating induces the polarization of water molecules within dielectric substances at specific frequencies, facilitating its utilization [17]. This process is complex and influenced by factors including dielectric properties, material size, form, and microwave design [28], [29]. Utilizing multimode designs, common in both commercial and household microwave ovens, materials are subjected to numerous resonant modes within metal cavities or enclosures [27]. Such microwave applicators allow for efficient and green thermal processing.

Background of the Neural Network

Since the 1940s, when the concept of networks made up of simple neuron models could perform computations [22], neural network techniques have advanced greatly and have been successfully used in various fields, such as learning, pattern recognition, signal processing, modeling, and system control. The use of neural networks in nonlinear system identification and control is largely motivated by their major benefits of highly parallel structure, learning capacity, nonlinear function approximation, fault tolerance, and efficient analog VLSI implementation for real-time applications [23]. Numerous nonlinearities, unmodeled dynamics, unmeasurable noise, and multiloop, among other factors, are present in many real-world systems, making it challenging for engineers to apply control schemes.

Modern and traditional control theories have served as a major foundation for the creation of new control tactics over the past few decades. The linearization of systems has served as the foundation for many contemporary control theories, including classical control theory and adaptive and optimal control techniques. Mathematical model building is a prerequisite for the deployment of such strategies. In contrast to conventional control techniques, the use of neural networks for control has generated significant research interest for several reasons. Neural networks can be trained to learn any function, thereby eliminating the need for complex mathematical analysis dominant in many traditional adaptive and optimal control methods. Additionally, the inclusion of activation functions in the hidden neurons of multilayered neural networks offers nonlinear mapping ability for solving highly nonlinear control problems where traditional control approaches have no practical solution yet [24].

Heat Transfer Mechanism

Microwave heating operates through the interaction of electromagnetic waves with materials, particularly polar molecules like water, inducing rapid molecular movement and generating heat.

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Conduction, convection, and radiation constitute the primary heat transfer mechanisms in microwave heating [33], [34]. Conduction involves the transmission of heat within a material via molecular vibrations and collisions [35]. In microwave heating, the oscillation of polar molecules causes rapid thermal energy generation, facilitating conduction through the material [36]. The rate of conduction depends on the material's thermal conductivity and the temperature gradient within it. Convection, observed in fluids, results from fluid movement transmitting heat.

Microwaved materials experience convection as heated portions become less dense and ascend while cooler regions descend, creating circulation that aids heat distribution [37]. Convection mechanisms can be natural or forced, driven respectively by buoyancy forces or external interventions like fans or pumps [33], [38]. Radiation, a medium-less heat transfer, involves the emission of thermal energy via electromagnetic waves [39]. In microwave heating, absorbed microwave energy is converted to thermal energy, which is subsequently emitted as radiation. The rate of radiation transmission depends on material emissivity, temperature differential, and surface area [33]. Microwave heating relies on the resonant absorption of electromagnetic waves, prompting molecular motion and subsequent heat generation. Conduction, convection, and radiation collectively facilitate efficient heat transfer within materials, underpinning the effectiveness of microwave heating methodologies.

METHODOLOGY

Mathematical explanation of the 10-Channel Microwave Oven.

The multi-feed port microwave heating model is simplified by assuming: (1) The heated medium's physical structure remains unchanged; (2) The medium starts with a uniform and isotropic temperature; (3) Its thermodynamic properties remain constant, though its dielectric properties may vary with temperature; (4) Air does not absorb microwaves or convert them into heat during the heating process.[40]

Let us denote the power of each magnetron P_i, where $\boldsymbol{i}$,ranges from 1 to 10, representing the 10 magnetrons. The energy output from each magnetron enters the microwave oven cavity through different waveguides and is multiplied by different coefficients, denoted as C_i. The total electromagnetic field energy entering the microwave oven cavity can be calculated as the sum of the electromagnetic field energy of the 10 channels.

$$\text{Total Energy} = \sum_{i=1}^{10}(P_{iMax} \times C_i \times R_i) \quad (1)$$

The conductive heat Transfer described by

$$\rho C\rho \frac{\partial T}{\partial t} = \nabla(k\nabla T) + Q \quad (2)$$

where ρ is the density, and $C\rho$ is the thermal capacity, k is the thermal conductivity, t is time, and T is temperature. The electric field is following

$$Q(x,t) = \frac{1}{2}\omega\varepsilon_0\varepsilon''|E(x,t)|^2 \quad (3)$$

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The Control System of the RBF Neural Network.

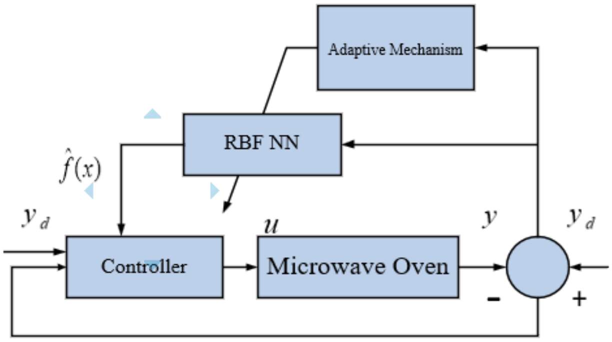

Figure 1: Block Diagram of the RBF Neural Network Control System

Now, from (1), (2), (3), Approximate it as a simplified dynamic system

$$\dot{T} = f(T, K) + U \tag{4}$$

Where, T is temperature, U is input like C_i,R_i. Equation can be written as

$$\dot{x} = f(x) + U \tag{5}$$
$$y = x \tag{6}$$

Where, $f(x)$ is unknown function.
This system can also be approximated as a nonlinear discrete system

$$y(k+1) = f(x(k)) + U(k) \tag{7}$$

Where $x(k) = [y(k)y(k-1)\cdots y(k-n+1)]^T$ is the state Vector, $U(k)$ is the Control input $y(k)$ is the Output.

In this section, we use RBF to design $\hat{f}(x)$ to approximate $f(x)$.The algorithm of RBF is described as

$$h_j = g\left(\left\|x - c_{ij}\right\|^2 / {b_j}^2\right) \tag{8}$$
$$f = W^T h(x) + \varepsilon \tag{9}$$

where x is the input vector, i denotes input neural nets number in the input layer j denotes hidden neural nets number in the hidden layer, $h = [h_1 h_{2,}, \ldots, h_n]^T$ denotes the output of hidden layer w is weight value ε is approximation error$|\varepsilon| \le \varepsilon_N$,If we use an RBF neural network to represent the unknown nonlinear function f, the control law becomes

$$u = \frac{1}{g(x)}[-f(x) + \ddot{y}_d + K^T E] \tag{10}$$
$$\hat{f}(x) = \widehat{W}^T h(x) \tag{11}$$

where is $h(x)$Gaussian function $\widehat{W}$, is the estimated parameter for W. Figure 1 show the closed-loop neural-based adaptive control System scheme.

We choose the adaptive law as

$$\widehat{W} = -\gamma E^T pbh(x) \tag{12}$$

In neural network (NN) algorithms, the control law defines how the system should respond to achieve the desired result. Adaptive Law adjusts NN parameters to enhance performance in varying conditions, ensuring the model adapts to changes and optimizes its behavior, enhancing overall system robustness and efficiency.

Adaptive Neural Network Controller Stability Analysis:

For the closed system, the discrete-time Lyapunov function can be designed as

$$V(k) = {e_1}^2(k) + \gamma\widetilde{w}^T(k)\widetilde{w}(k) \tag{13}$$

The first difference is

$$\begin{aligned}\Delta V(k) &= V(k) - V(K-1)\\ &= e_1^2(k) - e_1^2(k-1) + \gamma(\widetilde{w}^T(k) + \widetilde{w}^T(k-1))(\widetilde{w}^T(k) - \widetilde{w}(k-1)\end{aligned} \tag{14}$$

The stability proof is given with the following three steps. Firstly, using for $e_1(k-1)$ it follows that

$$\begin{aligned}\Delta V(k) &= e_1^2(k) - \frac{e_1^2(k) + \beta^2(\tilde{f}(x(k-1)) - v(k))^2 - 2\beta(\tilde{f}(x(k-1)) - v(k))e_1(k)}{C_1^2}\\ &= -V_1 + \frac{2\beta(\tilde{f}(x(k-1)) - v(k))e_1(k)}{C_1^2} + \gamma(\Delta\widetilde{w}^T(k) + 2\widetilde{w}^T(k-1))\Delta\widetilde{w}(k)\end{aligned} \tag{15}$$

Were, $V_1 = \frac{e_1^2(k)(1-c_1^2)}{c_1^2} + \frac{\beta^2(\tilde{f}(x(k-1)) - v(k))^2}{c_1^2} \geq 0$

Secondly, substituting for $\tilde{f}(x(k-1)$

$$\begin{aligned}\Delta V(k) &= -V_1 + \frac{2\beta\left(-\widetilde{w}(k-1)^T h(x(k-1)) - \Delta_f(x(k-1)) - v(k)\right)e_1(k)}{C_1^2} + \gamma\Delta\widehat{w}^T(k)\Delta\widehat{w}(k)\\ &\quad + 2\gamma\widetilde{w}^T(k-1))\Delta\widehat{w}(k)\\ &= -V_1 + 2\widetilde{w}^T(k-1)\left(\gamma\Delta\widehat{w}(k) - \frac{\beta}{C_1^2}h(x(k-1))e_1(k)\right) - \frac{2\beta}{C_1^2}(\Delta_f(x(k-1)) + v(k)e_1(k) + \gamma\Delta\widehat{w}^T(k)\Delta\widehat{w}(k)\end{aligned} \tag{16}$$

Thirdly, substituting the adaptive law for $\Delta V(k)$

The auxiliary signal $v_1(k)$ must also be designed so that $e_1(k) \rightarrow 0$ could deduce $e(k) \rightarrow 0$.The auxiliary term is designed as

$$v(k) = v_1(k) + v_2(k) \tag{17}$$

Where, $v_1(k) = \frac{\beta}{2\gamma c_1^2} h^T(x(k-1))h(x(k-1))e_1(k)$,and $v_2(k) = Ge_1(k)$

Structure of the Neural Network

The Radial Basis Function (RBF) neural network, comprising an input layer, hidden layer, and output layer, serves as a foundational element in control systems [22]. Input variables, such as sensor readings or error signals, are fed into the input layer, while a cluster of radial basis functions within the hidden layer transforms the input data into a higher-dimensional space. Subsequently, the output layer utilizes these transformed inputs to generate control signals or actions. The paper critically evaluates existing research [23], aiming to bridge identified gaps and contribute to the advancement of microwave heating control through insights gained from the proposed Neural Network Control (NNC) system.

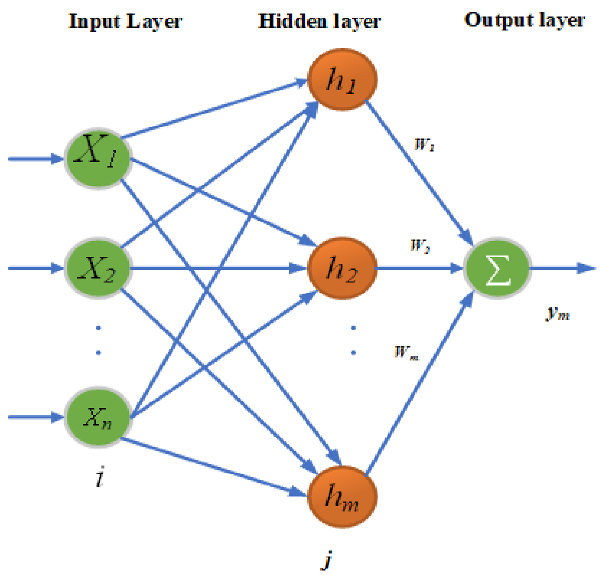

Figure 2: Structure Diagram of RBF Neural Network

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Block Diagram of the RBF Neural Network with a 10-Channel Microwave Oven

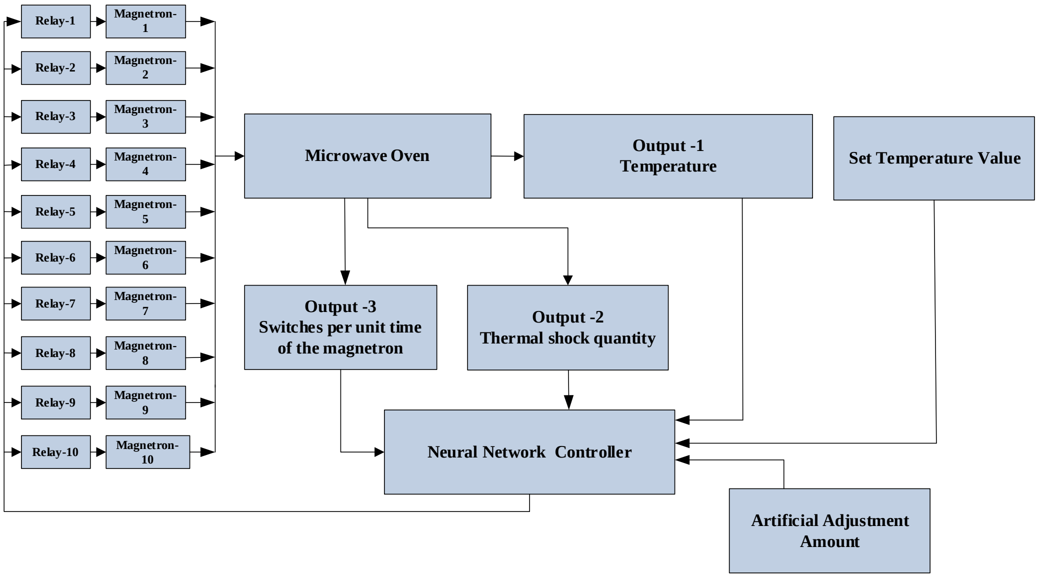

Figure 3: Function Diagram of NNC with a 10-Channel Microwave Oven

The relay acts as the main control hub, managing the activation of 10 distinct relays, each linked to a magnetron that generates microwaves for heating. These magnetrons send electromagnetic energy into the oven via waveguides. The microwave oven's space is where sample is heated by this energy. The system tracks the oven's temperature, the thermal shock (variation in energy input over time), and the magnetrons' switching frequency. Desired heating temperature and an artificial adjustment factor are fed into the system to fine-tune its performance. A neural network controller analyzes these variables, directing the relay controller to adjust operations, ensuring the oven function as intended.

Simulation Model and Implementation

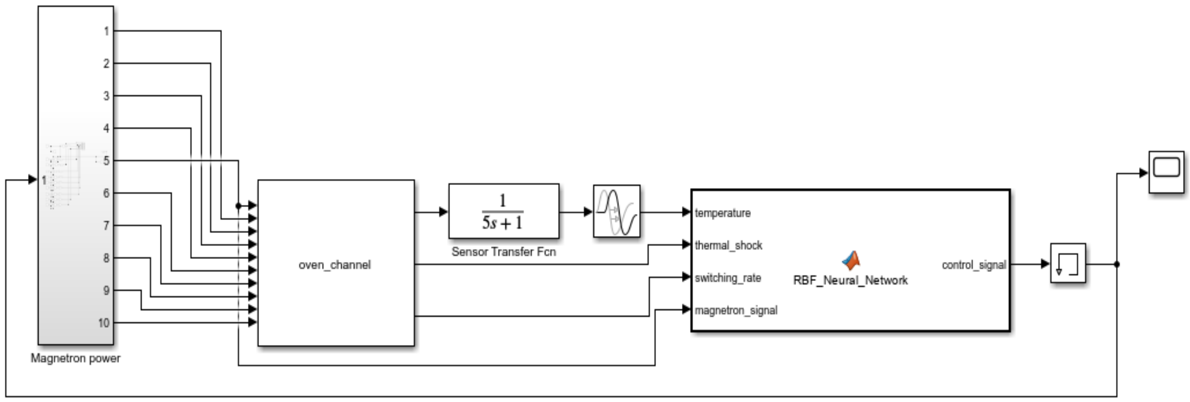

Figure 4: Simulink Model of NNC 10-Channel Microwave Ove

This section outlines a neural network controller connected to a microwave oven with 10 channels. It explains the system within a research context, highlighting how the Relay Controller autonomously

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activates and deactivates 10 relays, each linked to a magnetron, to independently control power. The magnetrons emit energy into the oven cavity, where food is heated. Temperature is monitored by a sensor, influencing relay control based on three outputs: internal temperature, thermal shock (differential energy input over time), and magnetron switching frequency. These feedback signals enable precise thermal management and energy distribution, demonstrating the system's intricate control mechanism over the heating process.

The Power Control System's Structure Diagram

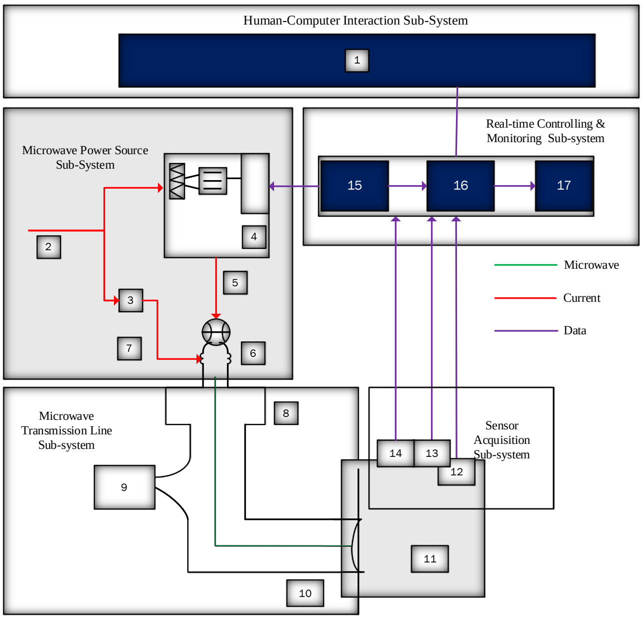

Figure 5: MW Oven's Power Control System Structure Diagram

The key components and subsystems of the machine, detailing their roles and interactions. The machine comprises several integral parts including: 1) the Computer-software Interface for user interaction; 2) the 220V AC power supply; 3) a Voltage Conversion Module for transforming 220V to 4V; 4) a High Voltage Module for generating up to 4000 Volts; 5) the Magnetron, responsible for microwave generation; 6) the Filament Current essential for the magnetron's operation; 7) The Waveguide directing microwaves; 8) a Matched Load to absorb microwaves without reflection; 9) a Dual-Directional Coupler for directing microwaves; 10) a Resonant Cavity for efficient microwave resonance; 11) a Temperature Sensor for real-time monitoring; 12) a Microwave Power Meter to measure power levels; 13) a Carbon Monoxide Sensor for safety; 14) an STM32 microcontroller for intelligent control; and 15) connectivity to a PC for data handling and control.

Focusing on the microwave generation and transmission, the Magnetron, powered by the High Voltage Module and regulated by the Voltage Conversion Module, is central to producing microwaves. These microwaves are then guided via the Waveguide to the Dual-Directional Coupler, and into the Resonant Cavity, with a Matched Load ensuring efficient power transfer without back reflection.

This setup is crucial for the controlled heating of materials within the cavity. For sensing and control, the Temperature Sensor and Microwave Power Meter are vital for monitoring the process in real-time, ensuring optimal performance. The system's process to the STM32 microcontroller, interfaces with these sensors to regulate the process based on real-time data, maintaining efficiency and safety. Lastly, the power subsystem intricately manages the flow of electricity from the 220V AC input through conversion stages, ensuring the Magnetron receives the correct voltages for its operation, highlighting the sophisticated engineering behind microwave generation and control. This entire setup showcases the complex interplay between electrical components and software control necessary for precision microwave heating applications. [31,32]

Implementation Temperature Control & Monitoring

The practical configuration of this project's temperature management and monitoring system for an industrial microwave oven. An STM32F407ZG MCU is used to manage the temperature of a K-type thermocouple sensor within the microwave oven. A MAX6675 amplifier module, ST-Link USB debugger, 24V DC output power supply, and relay module are among the other hardware components. For monitoring the temperature of the MW oven, I additionally used the NN control algorithm and UART Assist software. In this section, I describe the realistic setup and show two images of the temperature control and monitoring system.

Figure 6: Realistic View of the Control and Monitoring of the MW Oven

DATA ANALYSIS AND RESULTS

The In this part, we have presented and described the results of microwave oven temperature control and monitoring in different steps. Two primary sections delve into the results and implications of the work, providing a comprehensive understanding of the research findings.

Output Result in Different Steps

Initially, presented the output result Respectively (Preliminary theoretical results, theoretical optimization results, preliminary experimental results, Experimental optimization results) of the adaptive RBF microwave oven temperature control system for Single input and a single output.

Preliminary theoretical results: The adaptive RBF microwave oven control system's preliminary theoretical output graph for single input and single output to control the temperature of the microwave oven in Figure 7.

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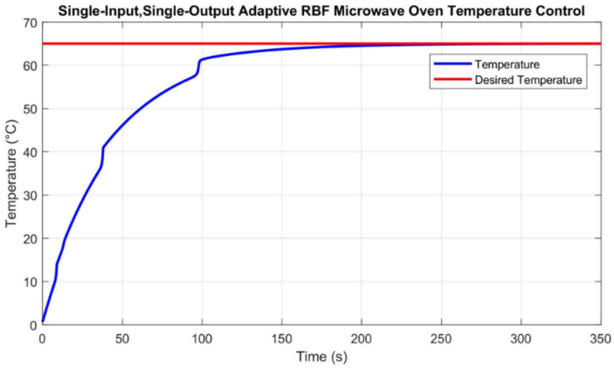

Figure 7: Output for Single -Input and Single Output Adaptive RBF MWO Temperature Control when Learning Period is Low

When the learning period of the RBF Control System is low, the output temperature gradually increases and reaches the desired temperature equality at a sampling time of 200 seconds.

Theoretical optimization results: In single input and single output systems here, present theoretical optimization output results. When the RBF NN learning period is increased to the maximum level, the output temperature reaches the equality state of the desired temperature in a very short time of sampling Time 100 seconds which is presented in Figure 8.

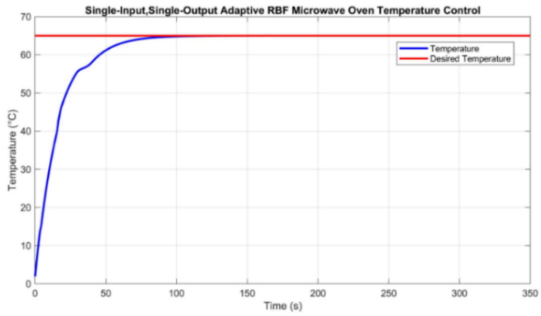

Figure 8: Single input and Single Output Adaptive RBF MWO temperature control output when the learning period is high

Preliminary experimental result: Now the comparative difference between simulation results and experimental results in this process is presented in Figures 9. Here we can see that at a temperature of 65°C and a sampling time of 200 seconds, the experimental temperature is equal to the desired temperature, so the simulation result and the experimental time difference between the 100 seconds.

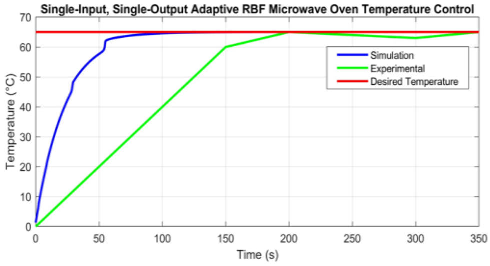

Figure 9: Comparison of the Simulation Graph With Experimental Result for Single- Input And Single-Output

Output Graph for Multivariate and Single Output

In a multivariate scenario involving the independent adjustment of 10 microwave inputs to regulate a single output—such as microwave temperature—the "Result" section delineates the consequences of manipulating these inputs on the targeted variable, namely microwave temperature. These inputs encompass parameters like power level and time settings. Within the "Result" section, here elaborate on how alterations in each of the 10 inputs influence microwave temperature. This analysis entails assessing the temperature's sensitivity to variations in each input, identifying optimal input combinations for specific temperature ranges, and discerning potential trade-offs or interactions among different input configurations. By elucidating the relationship between the 10 independent microwave inputs and the resultant temperature, the "Result" section facilitates the optimization and control of the microwave's performance. Also presented the output results of the Adaptive RBF Microwave Oven Temperature Control System for Multivariate and Single Output, alongside experimental findings at various stages. In this system, the gradual increase of the RBF NN learning period from zero ensures a smooth rise in output temperature, aligning the 50-second sampling time with the desired temperature.

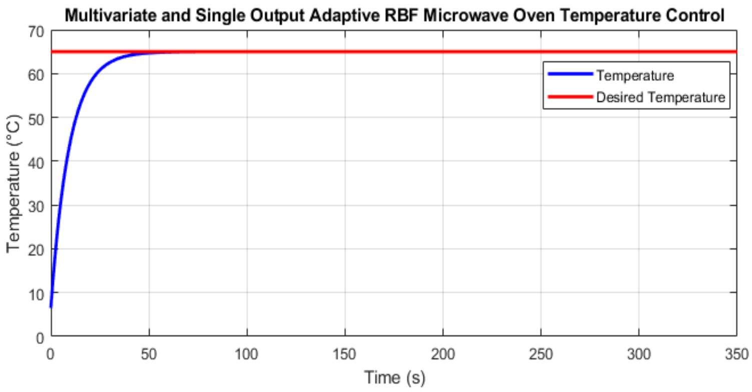

Figure 10: Multivariate and Single Output Adaptive RBF Microwave Oven Temperature Control System When Learning Periods Are Low

Here, how the output changes at a sampling time of 350 seconds is presented in Figures 10. In this section, the RBF System NN learning period is increased to the maximum, and as a result, the output temperature rises to the desired temperature after only 45 seconds of sampling time, which is presented in Figure 11.

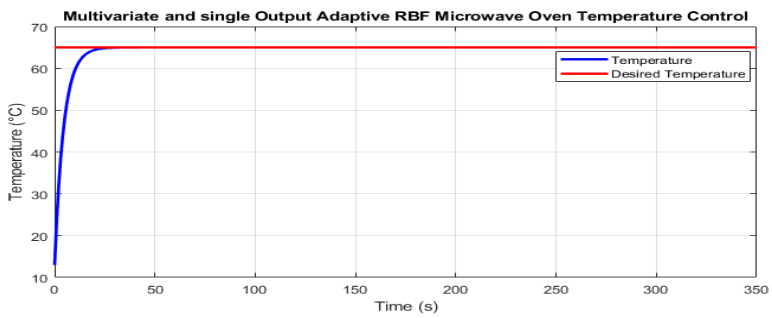

Figure 11: Multivariate and Single Output adaptive RBF MWO Temperature Control System When the Learning Period is High.

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Here, we can see that the desired output temperature is obtained from this system in a very short time. Experimental optimization results: In this part, the comparative difference between the simulation result and the experimental result has been seen in the mentioned system, which is presented in Figures 12. here saw that the simulation temperature reaches the equilibrium state of the desired temperature in 250 seconds for the sampling time of 350 seconds, and the experimental result smoothly reaches the equilibrium state of the desired temperature in 310 seconds, so the time delay between the simulation, and the experimental result is only 60 seconds, which indicates the quality of the result.

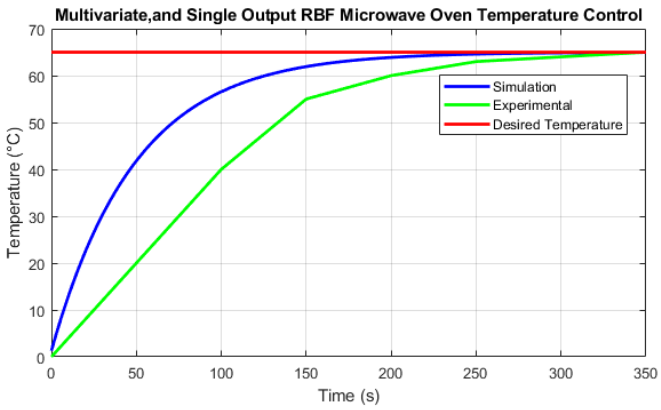

Figure 12: Comparison of The Simulation Graph with Experimental Result for Multivariate and Single output.

CONCLUSION AND RECOMMENDATIONS

Conclusion

The research objectives have been met, with a strong emphasis on ensuring experiment safety, particularly through the use of water as the primary medium. Noteworthy is the employment of K-type temperature sensors, expanding the measurement range to 1000 degrees and thereby enhancing control precision. A 10KW, 10-channel microwave input autonomously heats water samples (30-100°C), distinguishing between heating objects and implementing segmented control for autonomous heating. This thesis thoroughly examines enhancing control precision in industrial microwave heating systems, revealing the limitations of conventional PID controllers and proposing innovative solutions. A mechanistic model of the microwave heating process is developed, transitioning from single-input, single-output to multiple-input, multiple-output configurations, enabling precise parameter refinement with intelligent algorithms. The practical implementation phase involves designing, developing, and testing a control and monitoring system for a 10-magnetron microwave oven, ensuring temperature regulation, energy efficiency, and water consumption control. Safety protocols limit the oven's temperature to below 100 degrees during experimentation, despite its capacity to reach 1000 degrees, ensuring laboratory safety. The thesis suggests further research avenues, including additional safety measures, algorithm optimization, sensor integration, and scalability considerations for broader industrial applications. The research introduces a groundbreaking adaptive control algorithm employing Radial Basis Function (RBF) neural networks for regulating the temperature of a 10-channel high-power industrial microwave oven. This algorithm leverages the adaptability of RBF neural networks to

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dynamically learn and optimize the heating process. By integrating this sophisticated control strategy, industrial microwave ovens are expected to achieve enhanced operational efficiency, optimize energy utilization, and refine overall process control in high-power scenarios.

Recommendation

Enhanced Safety Measures: Further research can explore additional safety measures to ensure the well-being of the experimental setup and operators. Optimization of Control Algorithms: Continued refinement and optimization of intelligent algorithms for even greater precision and efficiency in temperature control. Integration of Advanced Sensors: Exploration of advanced sensor technologies to enhance data collection and improve the system's overall performance. Scalability and Industrial Application: Consideration of the scalability of the proposed system for broader industrial applications, focusing on real-world implementation challenges and solutions.

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