Journal of Network Intelligence ©2024 ISSN 2414-8105
Taiwan Ubiquitous Information Volume **9**, Number **4**, November **2024**

Application of Fuzzy Reasoning Model in Smart Home Control of Internet of Thingsm

Zhi-Xian Yang*

Zhengzhou Railway Vocational & Technical College, Zhengzhou 451460, P. R. China
yzx_zzrvtc_1012@163.com

Chao Jiang

Zhengzhou Railway Vocational & Technical College, Zhengzhou 451460, P. R. China
mailjc53240341@163.com

Xiong-Wei Liu

College of Science and Technology
North-Chiang Mai University, Amphoe Mae Rim, Chang Wat Chiang Mai 50200, Thailand
ek9050@163.com

*Corresponding author: Zhi-Xian Yang

Received December 23, 2023, revised March 13, 2024, accepted July 20, 2024.

Abstract. *A common main controller for IoT smart home control systems is the Programmable Logic Controller (PLC). PLCs are used to control various home smart electrical devices such as refrigerators, lighting and thermostats. However, PLCs usually use discrete control algorithms, which may be insufficient for certain application scenarios that require high-precision control. For example, PLCs may not be able to provide sufficient accuracy for temperature or humidity control that requires continuous adjustment. Therefore, in order to improve the performance of the control system, this work proposes a robust fuzzy regression PID control model that can be used in PLC control modules for IoT smart home devices. Firstly, based on the fuzzy control principle, the relationship between the tuning parameters of the fuzzy PID controller and the controlled object is analysed. Secondly, a self-adjusting fuzzy PID control algorithm is proposed on the basis of the traditional fuzzy PID control theory, which can adjust the correction factor in real time according to the change of error. Then, the traditional robust estimation method is improved by adding the estimation of covariance parameter, and a robust fuzzy regression PID control model is obtained by combining the improved robust estimation with self-adjusting modified fuzzy PID, so as to reduce the interference effect of the anomalies on the smart home control system that will be the Internet of Things, and to obtain good control accuracy and stability. The experimental results show that compared with other similar control models, the proposed model can better improve the control accuracy and overcome the system oscillations, with a steady state error of only 1.21% and a maximum overshoot of only 0.08.*

Keywords: Internet of things; Robust estimation; PID; Fuzzy control; Linear regression; Covariance

1. **Introduction.** The background of the Internet of Things (IoT) smart home control stems from the rapid development of technology and people's demand for improved quality of life. With the maturity of IoT technology and the popularity of smart devices, home control systems are able to achieve smarter and more convenient management [1, 2]. Smart home control systems enable various devices, such as smart lamps, thermostats,

and security systems, to communicate and work together by connecting them [3, 4]. This provides users with the ability to remotely monitor and control home devices, which not only improves the comfort and convenience of living, but also enables the optimisation of energy management, helping to reduce energy consumption and improve efficiency. The driving force behind this also includes the rise of Artificial Intelligence, enabling systems to learn user habits and provide personalised services. Smart home control is set against the backdrop of evolving technology and society's quest for smart, convenient and sustainable lifestyles that integrate the home into the digital and intelligent age [5, 6].

In the IoT smart home system, PID (Proportional-Integral-Differential) control [7, 8] is widely used for the precise regulation of environmental parameters such as temperature, humidity, and light. Through the PID control algorithm, the system is able to sense various sensor data in real time, such as temperature sensors and humidity sensors, and then accurately control the home equipment according to the set values. In terms of temperature control, PID control ensures that the indoor temperature is stable within the set range, improving comfort and achieving energy efficiency at the same time. For lighting systems, PID control can adjust the light brightness according to the feedback from light sensors to achieve intelligent energy saving [9, 10]. In addition, PID control can be used to monitor and control water quality and air quality in smart homes. However, with the continuous development of IoT technology, PID control is also evolving in smart home systems, combining machine learning, deep learning and other technologies [11] to better adapt to user habits and improve the system's intelligence.

The combination of fuzzy theory [12] with PID control algorithms has made significant progress in control systems. The purpose of introducing fuzzy logic into PID control is to improve the adaptability and robustness of the system to nonlinear and complex systems. By fusing the flexibility of fuzzy control and the stability of PID control, it can better cope with the uncertainties and variations that exist in real systems. In real-world applications, fuzzy PID control is commonly used for precise control of environmental parameters such as temperature and humidity [13, 14]. Fuzzy control is capable of handling ambiguous and uncertain environmental conditions, while PID control provides the advantages of fast response and precise control. For example, in smart home systems, fuzzy PID control enables better regulation of equipment such as air conditioning and heating systems [15] to meet the user's individual needs for indoor environments. In addition, fuzzy PID control is also widely used in industrial automation, robot control and other fields. In these applications, fuzzy PID control algorithms can effectively cope with system dynamic changes and external disturbances, and improve system robustness and performance.

Overall, the combination of fuzzy theory and PID control provides a more flexible and intelligent regulation for the control system, which makes the system better adapted to a variety of working conditions and environmental conditions. This combination shows great potential in practical engineering applications and provides new ideas for the design and optimisation of adaptive control systems. Therefore, in order to improve the performance of the control system, this work proposes a robust fuzzy regression PID control model that can be used in PLC control modules for IoT smart home devices.

1.1. **Related Work.** The current research focus of PID control algorithms includes improving its performance through optimisation algorithms, enhancing its intelligence by combining machine learning and deep learning methods, as well as its application in nonlinear and time-varying systems, which is dedicated to further improving the applicability and robustness of PID control in practical engineering. Researchers are also exploring the integration of PID control with various control strategies, such as fuzzy logic and neural networks, to cope with more complex and variable practical control problems [16, 17].

For the automatic voltage regulator system, Panda et al. [18] proposed an improved PID controller design method using a hybrid optimisation algorithm to optimise the PID parameters. By comparing the experimental and simulation results, the authors verified the validity and superiority of the method, and made suggestions for further improvement and application. Rajinikanth and Latha [19] provides a comprehensive overview of various PID controller tuning methods, including analytical, heuristic and optimization-based approaches. It analyzes the advantages and limitations of different tuning techniques. The categorization and comparison of methods gives good guidance for selecting tuning algorithms. However, recent intelligent tuning methods are not fully covered. Krishnan and Karpagam [20] proposes an online auto-tuning PID control scheme. It first uses the least squares method to identify a FOPDT model of the process. Then PID parameters are tuned based on the identified model. This method simplifies tuning by using an analytical formula. But robustness issues under model-plant mismatch need to be considered. Sarhadi et al. [21] designed an anti-windup PID scheme to improve performance for a nonlinear process. Stability analysis is provided for the proposed controller. The simulation results demonstrate effectiveness in handling actuator saturation. However, only a specific process is considered and experimental verification is lacking. Vasant et al. [22] uses genetic algorithm and particle swarm optimization to determine optimal PID parameters for a thermoelectric cooler system. The data-driven optimization approach achieves better temperature control accuracy. But the computational cost is high and real-time implementation is difficult. Yang et al. [23] proposes using reinforcement learning to optimize PID control gains for quadrotor stabilization. It combines the simplicity of PID with the optimization capability of RL. The adaptive PID gains lead to better performance. However, the training process is time-consuming and the results may not generalize well.

By fusing the flexibility of fuzzy control with the stability of PID control, it can better cope with the uncertainties and variations that exist in real systems. Pi et al. [24] proposes a self-tuning PID controller using fuzzy logic to adjust PID gains online based on error and error rate. It achieves better setpoint tracking performance. The limitations are increased computation load and stability relies on appropriate fuzzy rule design. Rodríguez-Abreo et al. [25] uses an adaptive neuro fuzzy inference system to tune optimal PID gains. Singhal et al. [26] proposes an Adaptive Fractional Order Parallel Fuzzy Proportional-Integral-Derivative Controller (AFOPFPC) and investigated it on WMR to meet the above challenges. It provides a more automated tuning approach with good adaptability. However, it requires careful design of the inference system structure and membership functions.

1.2. **Motivation and contribution.** Existing fuzzy PID controllers described above often struggle to effectively adapt to rapidly changing or diverse operating conditions. This limitation is due to the static nature of their rule sets and membership functions, which may not adequately capture the dynamics of different systems or environments. In addition, existing fuzzy PID control algorithms may be insufficiently robust in the face of system parameter variations, external perturbations, or model uncertainties, resulting in degraded control performance. Therefore, in order to solve the above problems, a robust fuzzy regression PID control model is proposed. The main innovations and contributions of this work include:

(1) A self-adjusting fuzzy PID control algorithm is proposed on the basis of the traditional fuzzy PID control theory, which is capable of adjusting the correction factor in real time according to the error changes. The correction factor is self-adjusted by dividing the slope of the correction curve into two parts, coarse and fine.

(2) In order to improve the robustness while increasing the control accuracy, a self-tuning fuzzy PID control algorithm is proposed on the basis of the self-tuning fuzzy PID control algorithm, which is capable of adjusting the correction factor in real time according to the change of the error. Then, the traditional robust estimation method is improved by adding the estimation of covariance parameter, and the robust fuzzy regression PID control model is obtained by combining the improved robust estimation with the self-tuning modified fuzzy PID.

2. Introduction to the rationale.

2.1. Fuzzy control principles. With the increasing complexity of systems studied in the current control field, accurate mathematical models are often difficult to establish, and traditional control methods are unable to solve the new problems currently faced. However, in practical applications, engineers can take appropriate countermeasures to skilfully control a complex process with their rich practical experience. Researchers quantified the experience of engineers through fuzzy mathematics, which led to the formation of fuzzy control theory [27], and thus fuzzy control algorithms came into being. Fuzzy sets express human thinking and judgement processes in a relatively simple mathematical form.

In order to achieve control of nonlinear processes, fuzzy control systems need to calculate the output error and its rate of change. Figure 1 shows the schematic diagram of a conventional fuzzy controller. The front-end data input mainly uses A/D acquisition interface to complete the conversion of analogue data to digital quantization. The analogue output mainly uses the D/A module interface. The whole system forms a closed-loop structure.

In Figure 1, E denotes the system error, EC denotes the rate of change of the system error, both of which are quantified fuzzy variables, and U denotes the output fuzzy variable of the fuzzy controller. The main function of the fuzzification module is to compute the degree of affiliation based on a quantified input variable within the corresponding fuzzy set using the affiliation function on the corresponding domain range in order to convert the input variable into a fuzzy variable.

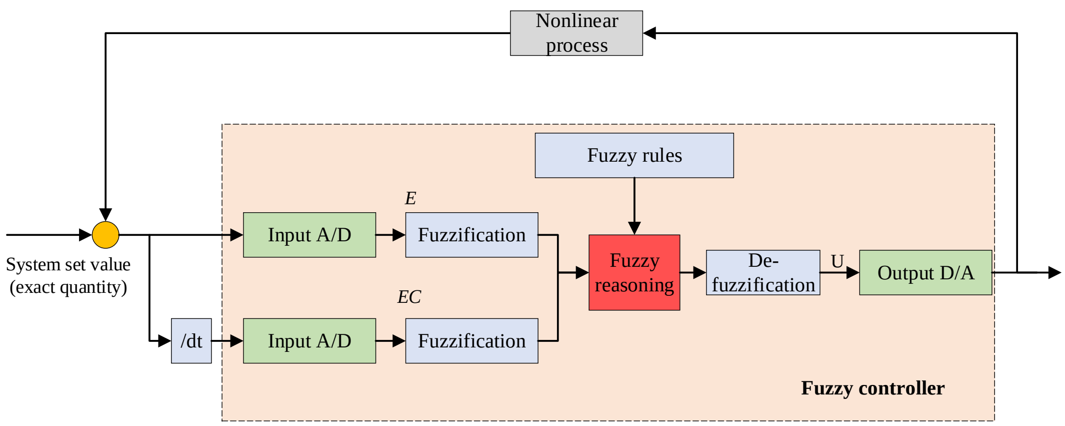

Figure 1. The schematic diagram of traditional fuzzy controller

A crucial part of the fuzzy controller is the fuzzy rules, which are mainly obtained through historical experience and expert analysis. The affiliation function used in the fuzzy inference module is shown in Figure 2. Since the outputs of the fuzzy inference module are still fuzzy variables, defuzzification operations are required.

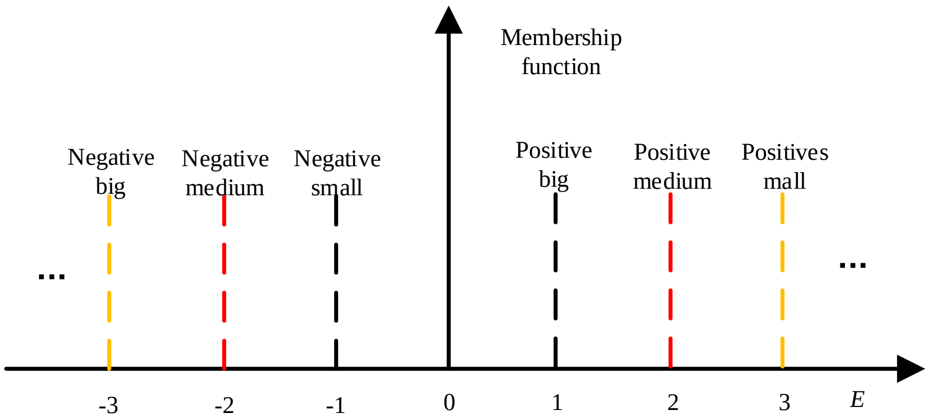

Figure 2. Fuzzy set of single output

For the fuzzification interface problem, the input computation of the fuzzy controller must be used for fuzzy inference by fuzzifying the error exact quantity e. Thus, the fuzzification interface is the input interface to the fuzzy controller, and its main role is to transform the real exact quantity into a fuzzy vector. A fuzzy subset of a fuzzy input variable can usually be classified as:

$$E = \{\text{NB, NS, ZO, PS, PB}\} \tag{1}$$

$$E = \{\text{NB, NM, NS, ZO, PS, PM, PB}\} \tag{2}$$

$$E = \{\text{NB, NM, NS, NZ, PZ, PS, PM, PB}\} \tag{3}$$

where NB denotes negative big; NM denotes negative medium; NS denotes negative small; NZ denotes negative zero; ZO denotes zero; PZ denotes zero positive; PS denotes positive small; PM denotes positive medium; PB denotes positive big.

The knowledge base is divided into two parts, including database and rule base. The database mainly stores quantification methods, rank selection, and affiliation functions of fuzzy subsets, which are set on the basis of engineers' experience and judgement with the subjectivity of engineering experience, and provide data to the reasoning machine during the fuzzy relational equation solving process of rule-based reasoning.

The rule base is set up based on expert knowledge or long-term accumulated experience of engineering operators, which is a linguistic expression of reasoning according to human intuition, usually connected by a series of relational words.

2.2. **Fuzzy PID controller.** In the traditional industrial field, it is still the classical PID algorithm that is heavily used, but the control effect depends on the accuracy of the identification model, and for the complex system where the controlled object is subject to load changes or disturbances, accurate modelling is often very difficult. With the continuous development of computer technology, fuzzy control algorithms have been widely popularised and used in recent years, and they have become one of the most active and mature technologies in the field of intelligent control technology, presenting superior performance to conventional control systems in many fields.

Fuzzy PID controllers have several structural forms, but their operating principles are basically the same [28]. The controller takes the error e and the error change ec as the input statement variables. Considering the stability, response speed, steady-state error, and overshooting amount of the system, the fuzzy rules are set in advance, and fuzzy reasoning is applied to adjust the PID parameters in real-time to meet the requirements of self-tuning of the PID parameters at different moments of e and ec, so as to improve the stability of the system. The structure of the fuzzy PID controller is shown in Figure 3.

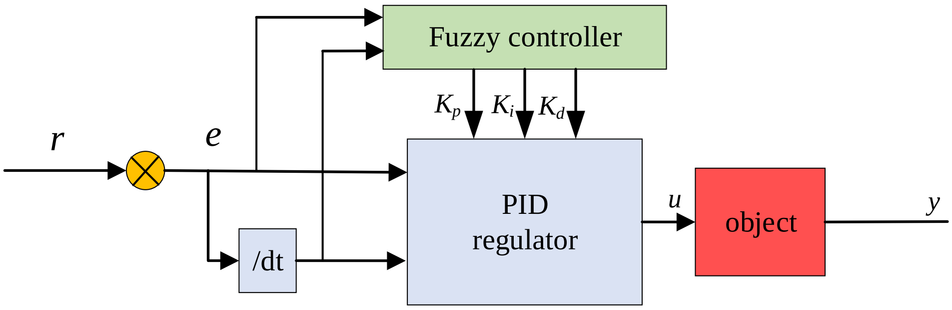

Figure 3. Structure diagram of fuzzy PID controller

The discrete fuzzy PID control algorithm is shown below:

$$u(k) = K_p e(k) + K_i T \sum_{j=1}^{k} e(j) + K_d \frac{e(k) - e(k-1)}{T} \tag{4}$$

Where k is the sequence of samples; T is the sampling time; K_p, K_i, and K_d are the PID tuning parameters.

In order to achieve Fuzzy PID parameters self-tuning, the first step is to find out the fuzzy relationship between the three tuned parameters of PID (K_p, K_i, K_d) and (e, ec). During the operation of the system, it is necessary to continuously sample and modify the three parameters online according to the fuzzy control principle to meet the requirements of the control parameters at different (e, ec). The control is carried out by considering the stability performance, response time, overshooting amount and steady-state accuracy of the system, so that the controlled object has good dynamic and static performance.

In this work, a fuzzy PID algorithm is introduced to regulate the PLC control of the IoT smart home model, which can better deal with the time-varying, non-linear and hysteresis problems in the system without the need of an accurate mathematical model, and has good robustness and the system response can be accelerated.

3. **The proposed self-regulating modified fuzzy PID control.** Fuzzy controllers have great application prospects and development potential in many fields. However, the fuzzy control algorithms of the control modules that come with most PLC control software at this stage are too simple, so the control performance sometimes cannot meet the demand for high precision. In addition, it is unable to deal with multivariable, nonlinear and time-varying control requirements.

Therefore, in order to solve this problem, a self-adjusting fuzzy PID control algorithm is proposed on the basis of the traditional fuzzy PID control theory, which is able to adjust the correction factor in real time according to the change of error. The correction factor is self-adjusted by dividing the slope of the correction curve into two parts, coarse and fine.

In this paper, a simplified fuzzy control rule is used to implement the control algorithm, which is expressed as shown below:

$$U = \langle aE + (1-a)EC \rangle \quad a \in [0,1] \tag{5}$$

where a denotes the moderating correction factor; E, EC and U are all quantified fuzzy variables as described in the previous section.

Firstly the quantified fuzzy variables are made to have the same classification level as follows.

$$E = EC = U = [-N, ..., -3, -2, -1, 0, 1, 2, 3, ..., N] \tag{6}$$

The effect of the system error E and the rate of change of the system error EC on the output fuzzy variable U of the fuzzy controller can be realised by modifying the value of the adjustment correction factor a, i.e., adjusting a means adjusting the control rule. In general, the self-adjustment of the adjustment correction factor a is as follows:

$$a = \frac{(a_H - a_L)|E|}{N} + a_L \quad a_L \leq a \leq a_H \leq 1 \tag{7}$$

where the moderating correction factor $a \in [a_L, a_H]$.

Equation (7) embodies fuzzy quantitative control rules with self-regulating factors in the full range, i.e., it describes the self-regulation of weights (control outputs) according to the error values. This approach is easy to implement and has better real-time performance, reflecting the key role of human thinking in the control decision-making process. However, we can see that there is no EC fuzzy variable in Equation (7). Therefore, in the process of regulating the correction factor a of this method, the error change fuzzy variable EC cannot have any influence on it, which leads to the performance of this method cannot be further improved.

In order to improve the performance of the traditional fuzzy PID control algorithm, this paper divides the self-adjustment of the regulation correction factor a into two components, coarse and fine, and realises the self-adjustment by combining the two. Among them, the main idea of fine regulation is to adjust the curve of regulation correction factor a in real time according to the change of system error E. The formula for real-time adjustment of a is as follows:

$$a = |E| \cdot |k + E_m k_m + a_m| \tag{8}$$

where k denotes the slope of the correction curve in the region of the unit step response at this point in time; a_m and E_m denote the horizontal and vertical coordinates of the centre point where the change in slope is the rotation of the correction curve.

Coarse adjustment is the process of adjusting the slope to quantitatively analyse the amplitude of the oscillation by calculating the maximum error rate of change, i.e., to achieve the systematic error rate of change EC is taken into account in the process of adjusting a. The slope k is adjusted in coarse adjustment in the following way:

$$k = \frac{k'_{max}}{N} k_0 \tag{9}$$

where k_0 denotes the initial slope; k'_{max} denotes the maximum error rate of change (belonging to the previous response phase).

By combining Equation (8) and Equation (9), we can derive the adjustment correction factor a for the coarse-fine combination, which can be expressed as follow:

$$a = \frac{|E| \cdot k'_{max}}{N} k_0 + \frac{E_m k'_{max}}{N} k_0 + a_m \tag{10}$$

In this paper, we propose the self-regulating correction factor fuzzy PID controller as shown in Figure 4. Z^{-1} denotes the delayed operation of the control quantity at the previous moment in order to complete the calculation of the maximum error rate of change of the previous response stage in coarse regulation.

4. **The proposed robust fuzzy regression PID control model.**

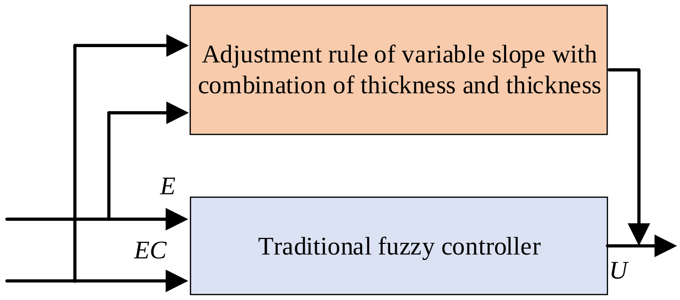

Figure 4. Proposed Self-Tuning Modifier Fuzzy PID Controller

4.1. **Linear regression principle analysis.** Existing PID controls are all very sensitive to abnormal data points, and too many abnormal data points will significantly reduce the control accuracy and reliability. Although the proposed self-tuning modified fuzzy PID control can effectively improve the control accuracy, the robust estimation capability is still unsatisfactory. This is due to the fact that most of the regulation processes only calculate the mean parameter without considering the influence of the covariance parameter, thus ignoring the negative effect of outliers [29]. It is well known that fuzzy linear regression has strong stability.

Therefore, this paper improves the traditional robust estimation method, increases the estimation of covariance parameter, and combines the improved robust estimation with self-adjusting modified fuzzy PID to obtain a robust fuzzy regression PID control model, so as to reduce the influence of anomalies on the interference of will IOT smart home control system, and to obtain good control accuracy and stability.

At present, regression analysis methods are mainly divided into linear regression and non-linear regression, and the main content of this paper is the linear regression analysis method. The control principle based on linear regression analysis is shown below:

$$y(t) = b_0 + b_1 x_{i_1} + b_2 x_{i_2} + \cdots + b_p x_{ip} + \Theta(t) \tag{11}$$

where $y(t)$ denotes the control value at time t; x_{ip} denotes the various factors associated with the control, i.e., the random independent variables; b_p denotes the regression coefficients of the regression equation; $\Theta(t)$ denotes the random disturbances, which are generally those obeying a normal distribution.

4.2. **Basic model of fuzzy linear regression.** Fuzzy linear regression is a regression analysis method based on fuzzy logic [30]. It is a combination of fuzzy inference theory and linear regression model.

In traditional linear regression models, a linear relationship is assumed to exist between input variables and output variables. In fuzzy linear regression, on the other hand, the relationship between input and output variables can be fuzzy, considering the vagueness and uncertainty of many problems in the real world. Unlike traditional linear regression models, the regression coefficients in fuzzy linear regression are no longer definite values, but fuzzy numbers. A fuzzy number is composed of an affiliation function and a fuzzy set to describe the fuzzy relationship between the input and output variables.

By using fuzzy logic operations and fuzzy reasoning, the fuzzy values of the output variables can be obtained based on the fuzzy values of the input variables and the fuzzy numbers of the regression coefficients. Then, based on the characteristics of the fuzzy values and fuzzy set operations, the deterministic values of the output variables can be further obtained. Therefore, fuzzy linear regression has certain advantages in dealing with fuzzy and uncertainty problems. On the basis of linear regression analysis, the control model of short-term fuzzy linear regression is proposed by introducing the concept of fuzzy sets.

$$Y_i = A_0 + A_1 x_{i_1} + \cdots + A_p x_{ip} \quad (i = 1, 2, \ldots, n) \tag{12}$$

where A_j denotes the regression coefficient; A_j, x_{ij}, and Y_i are fuzzy numbers.

Traditional control methods based on linear regression analysis are simpler to implement and have fewer parameters. The control method based on fuzzy linear regression analysis improves the stability, but it is still more sensitive to the anomalies in the data, resulting in low robustness, which affects the applicability in practical application scenarios.

On the basis of the above control method based on fuzzy linear regression analysis, robust estimation theory is introduced in this paper in order to improve the robustness of control.

4.3. **Robust estimation.** The theory of robust estimation is a statistical method for estimating parameters in the presence of outliers or when the data deviate from a normal distribution. Traditional methods of parameter estimation, such as least squares estimation, are very sensitive to outliers and are prone to produce unstable estimates. Robust estimation theory aims to improve the stability and reliability of estimates by using robust estimation methods that reduce the impact of outliers on the estimation results.

The basic idea of robust estimation methods is to reduce the effect of outliers by weighting the data or using estimation functions with strong robustness. Assuming that the number of data sets is m, and the i-th parameter has n_i observed values, and a total of n observations are recorded, the observed results for the i-th parameter at moment t are shown below:

$$y_{ij} = x_{ij}^T \beta_0 + f_0(t_{ij}) + e_{ij} \tag{13}$$

where x_{ij}^T denotes a covariate; β_0 denotes a p-dimensional regression coefficient; $f_0(\cdot)$ denotes a smooth function; e_{ij} denotes an independently distributed disturbance obeying an ellipsoidal distribution.

The B-spline basis function is used to approximate $f_0(\cdot)$, then the linearisation formula is shown as follow:

$$y_{ij} = \left(x_{ij}^T, \pi^T(t_{ij})\right) \delta_0 + e_{ij} \tag{14}$$

$$\pi^T(t) = (B_1(t), B_2(t), \ldots, B_n(t))^T \tag{15}$$

where δ_0 denotes the joint regression parameters to be estimated.

4.4. **Improved Robust Estimation Based on Covariance Parameters.** In this paper, improved robust estimation equations are used to estimate the parameter δ_0 and the covariance parameter γ_0, respectively, as follows:

$$U_\delta(\delta, \gamma) = \sum_{i=1}^{m} D_i V_i^{-1/2}(\gamma) h_i(\delta, \gamma) = 0 \tag{16}$$

$$U_\gamma(\gamma, \delta) = \sum_{i=1}^{m} \left\{ \frac{K}{2} \left[W_i Z_i^{-1/2}(\gamma) \frac{\partial V_i(\gamma)}{\partial \gamma} - \frac{1}{2} h_i^T V_i^{-1/2}(\gamma) \frac{\partial V_i(\gamma)}{\partial \gamma} V_i^{-1/2}(\gamma) h_i \right\} \right] \tag{17}$$

where K denotes the factor that ensures robust estimation of the covariance parameter (in this paper, we set the disturbances to follow a normal distribution, hence, $K = 0.3$).

$$h_i = h_i(\delta, \gamma) = W_i \psi f(Z_i) \tag{18}$$

where W_i denotes the weights matrix; $\psi f(\cdot)$ denotes the Huber regression function.

Selecting the diagonal matrix as the weight matrix W_i, then $W_i = diag\{\omega_{i1}, \omega_{i2}, \ldots, \omega_{in}\}$.

$$\omega_{ij} = \omega\left(x_{ij}\right) = \min\{1, \left(\frac{b_0}{\left(x_{ij}-m_x\right)^T\left(x_{ij}-m_x\right)}\right)^{v/2}\} \tag{19}$$

where $v \geq 1$ is a constant.

In this paper, the use of covariance parameters to improve robust estimation has the following 2 benefits: (1) Considering the correlation between variables. The covariance parameter can reflect the correlation between variables. In robust estimation, the use of covariance parameters can more accurately describe the correlation structure of the data, thus improving the accuracy and reliability of the estimation. (2) Reduce the effect of outliers. The covariance parameter has a certain anti-interference ability to outliers. By considering the covariance relationship between variables, the impact of outliers on the estimation results can be reduced and the stability of estimation can be improved. The use of covariance parameters to improve robust estimation can improve the accuracy, stability and reliability of estimation. It can make more comprehensive use of the information in the data, reduce the impact of outliers, and improve the fit of the model. This is very helpful in dealing with outliers and correlation structures present in the actual data and improves the quality of the estimation results.

4.5. **Asymptotic properties analysis.** The asymptotic properties of f_0 and γ_0 are analysed next using multivariate normal variables.

Asymptotic property analysis is a method used in mathematics to describe the behaviour of a function at infinity. When we discuss the properties of a function as its independent variables tend to infinity, we are usually concerned with its asymptotic behaviour. Suppose the covariates X and t have the following relationship:

$$x_{ijk} = g_k\left(t_{ij}\right) + \delta_{ijk}, \quad 1 \leq i \leq m,\, 1 \leq j \leq n_i,\, 1 \leq k \leq p \tag{20}$$

where $g_k(t)$ denotes a bounded derivative of order r; δ_{ijk} is a normal distribution with mean 0 and independent of e_{ij}.

Theorem 1 If the assumptions made by Sinha are satisfied, including:

(1) The size of the data should tend to infinity, i.e. $n \to \infty$;

(2) The data should obey a specific probability distribution;

(3) The estimates should have a certain asymptotic distribution, i.e., they should obey a particular asymptotic distribution when the sample size is large enough.

Then the number of nodes $k_n \approx n^{1/(2\gamma+1)}$ for all estimates $\hat{f}$.

$$\frac{1}{n}\sum_{i=1}^{n}\left(\hat{f}(t_i) - f_0(t_i)\right)^2 = O_p\left(n^{-2\gamma/(2\gamma+1)}\right) \tag{21}$$

$$\sqrt{n}\left(\hat{\delta} - \delta_0\right) \xrightarrow{\Gamma} N\left(0, V_\delta\right) \tag{22}$$

where $V_\delta = K_\delta S_\delta K_\delta^{-1}$; K_δ denotes a positive definite matrix; $\xrightarrow{r}$ denotes convergence to a distribution.

It follows from **Theorem 1** that the improved robust estimation based on the covariance parameter has no significant suppression of the asymptotic nature of the construction.

4.6. **Steps of the control algorithm.** The proposed model is used to implement the control of IoT smart home electrical devices in the following steps:

Step 1: Estimate the initialised values of different parameters δ_0 and covariance parameter γ_0 according to the different requirements of smart home devices;

Step 2: Set $\gamma = \gamma_{(j-1)}$ and $\delta = \delta_{(j)}$ in the j-th iteration and follow Equation (16) and Equation (17) to solve for $\delta_{(j)}$ and $\gamma_{(j)}$ respectively;

Step 3: $j = j + 1$ and repeat step 2 until iteration to convergence, thus obtaining $\hat{\delta}$ and $\hat{\gamma}$;

Step 4: Detect the presence of outliers and classify them;

Step 5: Construct a robust fuzzy regression model, as shown below;

$$\min \int |\mu_Y(x) - \mu_{\hat{Y}}(x)| \; s.t. \; \hat{Y}_i \supseteq Y_i \tag{23}$$

where $\mu_Y(x)$ denotes the affiliation function of the fuzzy number Y.

Step 6: Equation (23) is solved by least squares method;

Step 7: Output robust fuzzy control intervals to meet the demand for high-precision and high-stability system control.

The robust fuzzy regression PID control model is shown in Algorithm 1.

Algorithm 1 Robust fuzzy regression PID control model (Part 1)

```
function RobustFuzzyRegressionPIDControl(error, previous_error, cumulative_error)
    fuzzy_error = FuzzyLogic(error)                    ▷ Fuzzy Logic Block
    Fuzzy Regression Block
    regression_coefficients = FuzzyRegression(fuzzy_error, previous_error, cumulative_error)
    PID Control Block
    proportional_term = regression_coefficients[0] * error
    integral_term = regression_coefficients[1] * cumulative_error
    derivative_term = regression_coefficients[2] * (error - previous_error)
    // Calculate control signal
    control_signal = proportional_term + integral_term + derivative_term
    return control_signal
end function
function FuzzyLogic(error)
    // Fuzzy logic rules and membership functions
    // Define fuzzy sets, linguistic variables, and rule base
    // Fuzzify the error and possibly other relevant variables
    // Apply fuzzy rules to get fuzzy error
    fuzzy_error = FuzzyInference(error)
    return fuzzy_error
end function
function FuzzyRegression(fuzzy_error, previous_error, cumulative_error)
    // Fuzzy regression rules and membership functions
    // Define fuzzy sets, linguistic variables, and rule base
    // Fuzzify fuzzy error, previous error, and cumulative error
    // Apply fuzzy regression rules to get regression coefficients
    regression_coefficients = FuzzyRegressionIn(fuzzy_error, previous_error, cumulative_error)
    return regression_coefficients
end function
```

function FuzzyInference(error)
    // Define inference rules to determine the degree of membership
    // in fuzzy sets based on error values
    // Use linguistic variables and rule base to infer fuzzy error
    return fuzzy_error
end function
function FuzzyRegressionIn(fuzzy_error, previous_error, cumulative_error)
    // Define inference rules to determine the regression coefficients
    // Use linguistic variables and rule base to infer regression coefficients
    return regression_coefficients
end function

5. Experimental Results and Analyses.

5.1. Experimental Equipment. The JT3U series single board PLC from YKHMI is used for the experiment. The hardware structure is mainly composed of CPU module, memory unit, power module and input/output interfaces. This is a small modular PLC which is widely used in the market. The devices such as PLC modules and smart homes in the IoT environment are connected through LoRa nodes for data acquisition. Multiple LoRa nodes are wirelessly networked via 433MHz licence-free band.

There are many models and specifications of JT3U series single board PLC mainframe, you can choose the appropriate model according to the actual needs. The selected PLC model is JT3U-48MRT-16MT, powered by 24V DC, containing 24-channel relay output, 8-channel transistor output, 10-channel AD analogue sampling channel, 2-channel DA digital output, supporting RS232 and RS485 interfaces, and its physical diagram is shown in Figure 5.

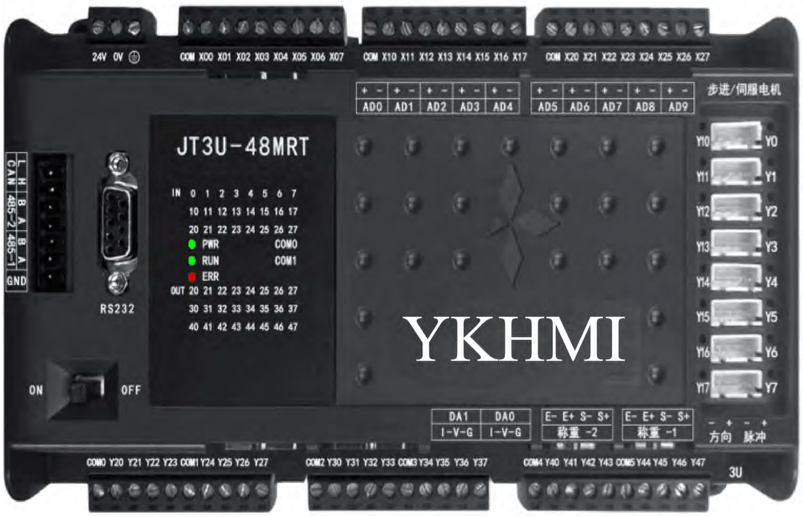

Figure 5. JT3U-48MRT-16MT module

5.2. Control performance analysis. In order to verify the advancement of the proposed Robust Fuzzy Regression PID Control (RFRPC), it was compared with Rule Self-Adjusting Fuzzy Control (RSAFC) and AFOPFPC [26]. The parameters of the 2 fuzzy controllers, K_u, K_e, and K_{ec} were set to 0.1, 5, and 45, respectively. The centre point of the rotation of the correction curve was set to 0.5 and the initial slope of the curve K_0 was set to 0.1333.

$$K_0 = \frac{2(a_H - a_L)}{N} \tag{24}$$

Example 1: The first control object selected is shown as follows:

$$G(s) = \frac{2.2s + 4.6}{s^2 + 4s + 3} e^{-3s} \tag{25}$$

Taking temperature control as an example, the three affiliation functions (cold, mild and hot) of the triangular affiliation function with centres and ranges of (0, 10, 20), (15, 25, 35) and (30, 40, 50) respectively. The number of rules in the fuzzy rule base is 10. Maximum affiliation method is used to calculate the final output values. The curve obtained from the test is shown in Figure 6. It can be seen that compared to RSAFC and AFOPFPC, the RFRPC model is able to improve the control accuracy better with a steady state error of only 1.21%. In addition, has a high response speed and better real-time performance.

Example 2: The control object selected again is:

$$G(s) = \frac{1}{1.6s^2 + 4.4s + 1} \tag{26}$$

The scanning period of the PLC module is set to 10 ms, the input/output refresh time is set to 5 ms, the communication rate is set to 9600 bps, the preset value of the timer is set to 500 ms, and the program memory is allocated to 20 KB. The curve obtained from the test is shown in Figure 7. It can be seen that the RFRPC model proposed in this paper can better overcome the perturbations occurring in the system, with small fluctuations, and the maximum overshoot is only 0.08.

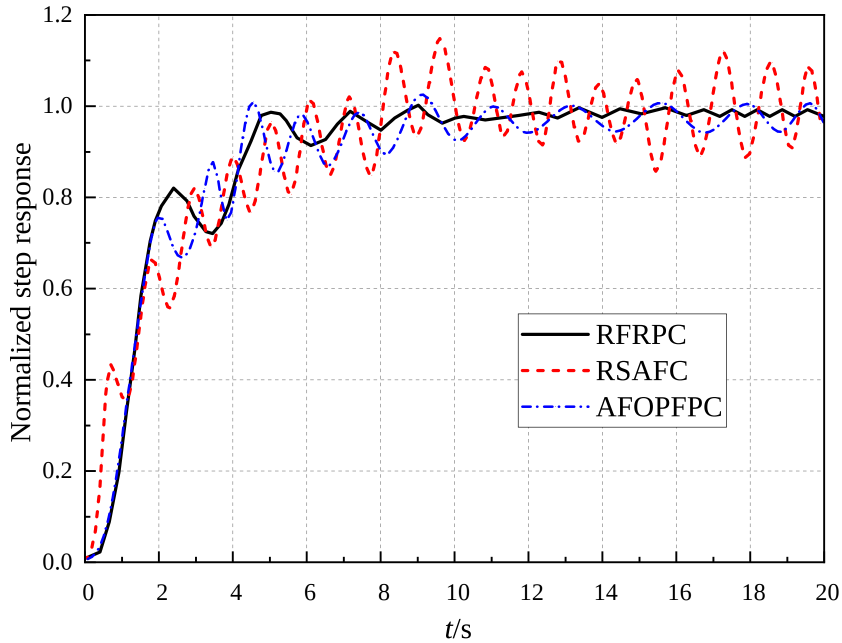

Figure 6. Comparison of Test Results for Calculation 1

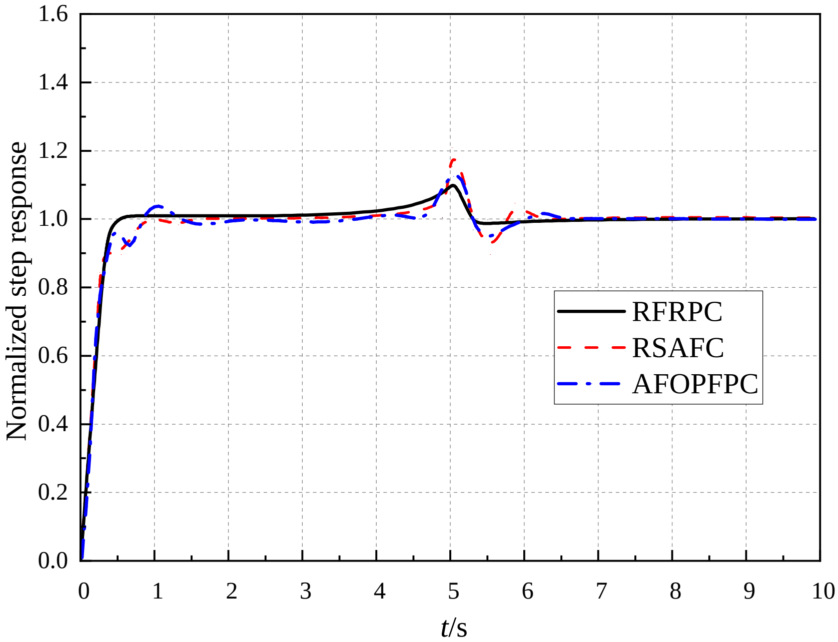

Figure 7. Comparison of Test Results for Calculation 2

6. **Conclusion.** In this work, a self-adjusting fuzzy PID control algorithm is proposed on the basis of the traditional fuzzy PID control theory, which is able to adjust the correction factor in real time according to the error change. The correction factor is self-adjusted by dividing the slope of the correction curve into two parts, coarse and fine. In addition, in order to improve the robustness while improving the control accuracy, a self-regulating fuzzy PID control algorithm is proposed on the basis of the self-regulating fuzzy PID control algorithm, which is able to adjust the correction factor in real time according to the error changes. Then, the traditional robust estimation method is improved by adding the estimation of covariance parameter, and the RFRPC model is obtained by combining the improved robust estimation with self-tuning modified fuzzy PID. The experimental results show that, compared with other similar control models, the proposed model can better improve the control accuracy and overcome the system oscillation, with a steady-state error of only 1.21% and a maximum overshoot of only 0.08, which better meets the demand for high-precision, steady-state control of IoT smart homes.

REFERENCES

[1] B. L. R. Stojkoska and K. V. Trivodaliev, "A review of Internet of Things for smart home: Challenges and solutions," *Journal of Cleaner Production*, vol. 140, pp. 1454-1464, 2017.
[2] M. Alaa, A. A. Zaidan, B. B. Zaidan, M. Talal, and M. L. M. Kiah, "A review of smart home applications based on Internet of Things," *Journal of Network and Computer Applications*, vol. 97, pp. 48-65, 2017.
[3] T. S. Gunawan, I. R. H. Yaldi, M. Kartiwi, N. Ismail, N. F. Za'bah, H. Mansor, and A. N. Nordin, "Prototype design of smart home system using internet of things," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 7, no. 1, pp. 107-115, 2017.
[4] W. Choi, J. Kim, S. Lee, and E. Park, "Smart home and internet of things: A bibliometric study," *Journal of Cleaner Production*, vol. 301, 126908, 2021.
[5] M. Khan, B. N. Silva, and K. Han, "Internet of things based energy aware smart home control system," *IEEE Access*, vol. 4, pp. 7556-7566, 2016.
[6] Z. Shouran, A. Ashari, and T. Priyambodo, "Internet of things (IoT) of smart home: privacy and security," *International Journal of Computer Applications*, vol. 182, no. 39, pp. 3-8, 2019.

[7] A. Kamilaris, A. Pitsillides, and V. Trifa, "The smart home meets the web of things," *International Journal of Ad Hoc and Ubiquitous Computing*, vol. 7, no. 3, pp. 145-154, 2011.
[8] E. Park, Y. Cho, J. Han, and S. J. Kwon, "Comprehensive approaches to user acceptance of Internet of Things in a smart home environment," *IEEE Internet of Things Journal*, vol. 4, no. 6, pp. 2342-2350, 2017.
[9] W. A. Jabbar, T. K. Kian, R. M. Ramli, S. N. Zubir, N. S. Zamrizaman, M. Balfaqih, V. Shepelev, and S. Alharbi, "Design and fabrication of smart home with internet of things enabled automation system," *IEEE Access*, vol. 7, pp. 144059-144074, 2019.
[10] S. Feng, P. Setoodeh, and S. Haykin, "Smart home: Cognitive interactive people-centric Internet of Things," *IEEE Communications Magazine*, vol. 55, no. 2, pp. 34-39, 2017.
[11] T.-Y. Wu, Q. Meng, Y.-C. Chen, S. Kumari, and C.-M. Chen, "Toward a Secure Smart-Home IoT Access Control Scheme Based on Home Registration Approach," *Mathematics*, vol. 11, no. 9, 2123, 2023.
[12] T.-Y. Wu, L. Wang, and C.-M. Chen, "Enhancing the Security: A Lightweight Authentication and Key Agreement Protocol for Smart Medical Services in the IoHT," *Mathematics*, vol. 11, no. 17, 3701, 2023.
[13] T.-Y. Wu, F. Kong, Q. Meng, S. Kumari, and C.-M. Chen, "Rotating behind security: an enhanced authentication protocol for IoT-enabled devices in distributed cloud computing architecture," *EURASIP Journal on Wireless Communications and Networking*, vol. 2023, 36, 2023.
[14] C.-M. Chen, Z. Chen, A. K. Das, and S. A. Chaudhry, "A Security-Enhanced and Ultralightweight Communication Protocol for Internet of Medical Things," *IEEE Internet of Things Journal*, vol. 11, no. 6, pp. 10168-10182, 2024.
[15] C.-M. Chen, Q. Miao, F. Khan, G. Srivastava, and S. Kumari, "Sustainable Secure Communication in Consumer-Centric Electric Vehicle Charging in Industry 5.0 Environments," *IEEE Transactions on Consumer Electronics*, 2023.
[16] D. Somwanshi, M. Bundele, G. Kumar, and G. Parashar, "Comparison of fuzzy-PID and PID controller for speed control of DC motor using LabVIEW," *Procedia Computer Science*, vol. 152, pp. 252-260, 2019.
[17] C.-T. Chao, N. Sutarna, J.-S. Chiou, and C.-J. Wang, "An optimal fuzzy PID controller design based on conventional PID control and nonlinear factors," *Applied Sciences*, vol. 9, no. 6, 1224, 2019.
[18] S. Panda, B. K. Sahu, and P. K. Mohanty, "Design and performance analysis of PID controller for an automatic voltage regulator system using simplified particle swarm optimization," *Journal of the Franklin Institute*, vol. 349, no. 8, pp. 2609-2625, 2012.
[19] V. Rajinikanth and K. Latha, "Setpoint weighted PID controller tuning for unstable system using heuristic algorithm," *Archives of Control Sciences*, vol. 22, no. 4, pp. 481-505, 2012.
[20] K. Krishnan and G. Karpagam, "Comparison of PID controller tuning techniques for a FOPDT system," *International Journal of Current Engineering and Technology*, vol. 4, no. 4, pp. 2667-2670, 2014.
[21] P. Sarhadi, A. R. Noei, and A. Khosravi, "Model reference adaptive PID control with anti-windup compensator for an autonomous underwater vehicle," *Robotics and Autonomous Systems*, vol. 83, pp. 87-93, 2016.
[22] P. Vasant, U. Kose, and J. Watada, "Metaheuristic techniques in enhancing the efficiency and performance of thermo-electric cooling devices," *Energies*, vol. 10, no. 11, 1703, 2017.
[23] R. Yang, Y. Liu, Y. Yu, X. He, and H. Li, "Hybrid improved particle swarm optimization-cuckoo search optimized fuzzy PID controller for micro gas turbine," *Energy Reports*, vol. 7, pp. 5446-5454, 2021.
[24] C.-H. Pi, W.-Y. Ye, and S. Cheng, "Robust quadrotor control through reinforcement learning with disturbance compensation," *Applied Sciences*, vol. 11, no. 7, pp. 3257, 2021.
[25] O. Rodríguez-Abreo, J. Rodríguez-Reséndiz, C. Fuentes-Silva, R. Hernández-Alvarado, and M. D. C. P. T. Falcón, "Self-tuning neural network PID with dynamic response control," *IEEE Access*, vol. 9, pp. 65206-65215, 2021.
[26] K. Singhal, V. Kumar, and K. Rana, "Robust trajectory tracking control of non-holonomic wheeled mobile robots using an adaptive fractional order parallel fuzzy PID controller," *Journal of the Franklin Institute*, vol. 359, no. 9, pp. 4160-4215, 2022.
[27] M. H. Barhaghtalab, M. A. Sepestanaki, S. Mobayen, A. Jalilvand, A. Fekih, and V. Meigoli, "Design of an adaptive fuzzy-neural inference system-based control approach for robotic manipulators," *Applied Soft Computing*, vol. 149, 110970, 2023.

[28] A.-T. Nguyen, T. Taniguchi, L. Eciolaza, V. Campos, R. Palhares, and M. Sugeno, "Fuzzy control systems: Past, present and future," *IEEE Computational Intelligence Magazine*, vol. 14, no. 1, pp. 56-68, 2019.

[29] J. Heo, J. Y. Lee, and W. Kim, "Bayesian information criterion accounting for the number of covariance parameters in mixed effects models," *Communications for Statistical Applications and Methods*, vol. 27, no. 3, pp. 301-311, 2020.

[30] M. G. Akbari and G. Hesamian, "A fuzzy linear regression model with autoregressive fuzzy errors based on exact predictors and fuzzy responses," *Computational and Applied Mathematics*, vol. 41, no. 6, 284, 2022.