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SYNTHESIS OF AN ADAPTIVE NEURO-FUZZY CONTROL SYSTEM FOR STEAM GENERATOR TEMPERATURE

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Abstract: *This paper is devoted to the modeling and synthesis of an adaptive neuro-fuzzy control system for steam generator temperature. Temperature control systems play an important role in industry because accurate and stable control is a prerequisite for the efficient operation of steam systems. Traditional control methods based on mathematical models and fixed parameter controllers may have limitations in providing optimal performance and adapting to changing operating conditions. The paper proposes a synthesized system combining fuzzy logic and adaptation methods to achieve more accurate and stable temperature control. A detailed structural diagram of the system, modeling, and tuning methods are presented. The results of the study can be applied to improve the efficiency and reliability of temperature control in steam generators in various industries. The proposed control system has the potential for application in various industrial sectors where accurate and adaptive temperature control of steam generators is required. It can help to improve process efficiency and reduce energy costs.*

Keywords: *Modeling, synthesized adaptive-fuzzy system, control, temperature, steam generator, industry, accuracy, stability, efficiency, mathematical models, regulators, adaptation, uncertainty, production.*

Annotatsiya: *Ushbu ish bug' generatori haroratini adaptiv neyro-noravshan boshqaruv tizimini modellashtirish va sintez qilishga bag'ishlangan. Haroratni boshqarish tizimlari ishlab chiqarishda muhim rol o'ynaydi, chunki aniqlik va barqarorlikni boshqarish bug' ishlab chiqarish tizimlarining samarali ishlashi uchun zaruriy shart hisoblanadi. Matematik modellar va parametrlarni boshqarish qurilmalariga asoslangan an'anaviy boshqaruv usullari optimal ishlashni ta'minlash va o'zgaruvchan ish sharoitlariga moslashishda cheklovlarga ega bo'lishi mumkin. Maqolada haroratni aniqroq va barqaror boshqarishga erishish uchun noravshan-mantiq va moslashish usullarini birlashtirgan sintezlangan tizim taklif etiladi. Tizimning tarkibiy tuzilmasi, modellashtirish va sozlash usullari keltirilgan. Tadqiqot natijalari turli sohalardagi bug' generatorlarida haroratni boshqarish samaradorligi va ishonchliligini oshirish uchun qo'llanilishi mumkin. Taklif etilayotgan boshqaruv tizimi bug' generatorlarining haroratini aniq va moslashuvchan boshqarish zarur bo'lgan turli sanoat tarmoqlarida foydalanish imkoniyatiga ega. Bu jarayonlarning samaradorligini oshirishga va energiya xarajatlarini kamaytirishga yordam beradi.*

Tayanch so'zlar: *modellashtirish, sintezlangan adaptiv-noravshan tizim, boshqaruv, harorat, bug' generatori, sanoat, aniqlik, barqarorlik, samaradorlik, matematik modellar, rostlagichlar, moslashish, noaniqlik, ishlab chiqarish.*

Аннотация: *Работа посвящена синтезу адаптивной нейро-нечеткой системы управления температурой парогенератора. В промышленности системы управления температурой играют важную роль, поскольку точное и стабильное управление является необходимым условием для эффективной работы паровых систем. Традиционные методы управления, основанные на математических моделях и регуляторах с фиксированными параметрами, могут иметь ограничения в обеспечении оптимальной производительности и адаптации к изменяющимся условиям эксплуатации. В работе предлагается синтезированная система, объединяющая нечеткую логику и методы адаптации, для достижения более точного и стабильного управления температурой. Представлены детальная структурная схема системы, методы моделирования и настройки. Результаты исследования могут быть применены для повышения эффективности и надежности управления температурой в парогенераторах в различных отраслях. Предложенная система управления имеет потенциал для применения в* *различных промышленных секторах, где требуется точное и адаптивное управление температурой парогенераторов. Она может способствовать повышению эффективности процессов и снижению энергетических затрат.*

Ключевые слова: *Моделирование, синтезированная адаптивно-нечеткая система, управление, температура, парогенератор, промышленность, точность, стабильность, эффективность, математические модели, регуляторы, адаптация, неопределенность, производство.*

Introduction

In modern industry, temperature control systems play an important role in ensuring optimal operation of steam generators. Accurate and stable temperature control is integral to the efficient operation of steam systems and to achieving the required production results. Temperature control systems play a key role in ensuring the stability and accuracy of the heating process in a steam generator. Traditional control algorithms based on mathematical models and fixed parameter controllers can have some limitations in providing optimal performance and adapting to changing operating conditions.

In recent years, considerable attention has been paid to the development of adaptive and fuzzy control systems, which can achieve more flexible and efficient temperature control. Adaptive systems have the ability to self-learn and adapt to variable conditions, while fuzzy logic allows the uncertainty and fuzziness of the input data to be taken into account. These systems reduce the influence of external disturbances and parameter variations on the control process, providing more accurate and stable temperature control.

Traditional methods of temperature control include the use of mathematical models and fixed parameter controllers. However, such approaches can have limitations in providing high control accuracy and adapting to changing operating conditions.

The purpose of this The aim of this paper is to develop and model a synthesised adaptive-fuzzy control system for steam generator temperature. The application of such a system can lead to the increase of accuracy and stability of control, as well as to the reduction of the influence of external perturbations and parameter changes on the heating process. influence of external perturbations and parameter changes on the heating process of the steam generator. This approach improves the adaptive properties of the system by combining fuzzy logic and adaptation methods with a reference model, which is a virtual representation of the real control object.

The study will present a detailed structural diagram of the synthesised adaptive-fuzzy control system and describe its modeling and tuning methods. This will make it possible to apply the developed system to improve the efficiency and reliability of temperature control in steam generators, which is of practical importance in various industries including power generation, chemical industry and manufacturing. The system model will be based on the mathematical foundations of fuzzy logic and adaptivity, which will achieve optimal control of steam generator temperature.

In recent years, a lot of research has been conducted in the modeling and synthesis of adaptive-fuzzy systems for steam generator temperature control. In this review, we consider a few key works dealing with this topic.

One of the early works that laid the foundation for adaptive fuzzy control of steam generator temperature was done by Shimomori and Maeda. In their study, an adaptive control system based on fuzzy logic was proposed to control the temperature in a steam generator. The results showed that the proposed system provides stable and accurate control over a wide range of operating conditions [1].

Another significant work was carried out by Gao and Chen. They proposed a modified adaptive-fuzzy control system for a steam generator based on the combination of adaptivity and fuzzy logic. Numerical simulation results showed that the proposed system provides higher control accuracy and better adaptation to changing operating conditions compared to conventional methods [2].

Also worth mentioning is Lee's work, in which a hybrid adaptive-fuzzy control system for steam generator temperature control was proposed. This system combines fuzzy logic with genetic algorithm to optimise the controller parameters. The results of the study showed that the proposed system provides better performance and more efficient temperature control [3].

More recent studies also include the application of neural networks in adaptive fuzzy temperature control systems for steam generators. For example, the work of Zhu et al. proposed a hybrid system combining fuzzy logic and deep neural networks for optimal temperature control. The results showed that this approach can achieve high control accuracy and better adaptation to variable conditions [4].

In general, the research on modeling and synthesis of adaptive-fuzzy control systems for steam generator temperature control continues to develop. Various methods such as fuzzy logic, adaptivity, genetic algorithms and neural networks are applied to improve the control efficiency and accuracy. However, there are still many problems that require further research, such as uncertainty accounting, optimisation of system parameters and integration with other aspects of steam systems.

Research Methods

The present work represents a new contribution in the field of modeling adaptive-fuzzy temperature control systems for steam generators. It builds on previous research and seeks to develop a synthesised system that will provide more accurate and stable temperature control as well as accounting for variable operating conditions and disturbances.

Considering the presented research results, a structural scheme of a modified adaptive-fuzzy steam generator temperature control system including a reference model has been developed as shown in Figure 1. This scheme is an integration of adaptivity and fuzzy logic to achieve accurate and stable control of steam generator temperature under different operating conditions.

The reference model is the key element in the system and is used to estimate the control error. It is a mathematical model of the steam generator based on physical principles and identified from experimental data. The reference model compares the output data with the desired values and generates the control error, which is then used to adjust the fuzzy logic parameters [5-7].

Fuzzy logic includes a set of fuzzy rules that define the relationship between the input and output variables of a system. It allows to take into account the uncertainty and vagueness of input data, which is especially important when dealing with steam generators where operating conditions may vary.

The adaptability of the system is realised by tuning the fuzzy logic parameters based on optimisation methods. The system parameters can be changed in real time to adapt to the changing operating conditions of the steam generator and provide optimal temperature control [8-12].

The developed structural scheme of a modified adaptive-fuzzy steam generator temperature control system is an innovative approach that achieves high control accuracy and stability. Its application can have a significant potential to improve process efficiency and reduce energy costs in industrial sectors where steam generators are key components.

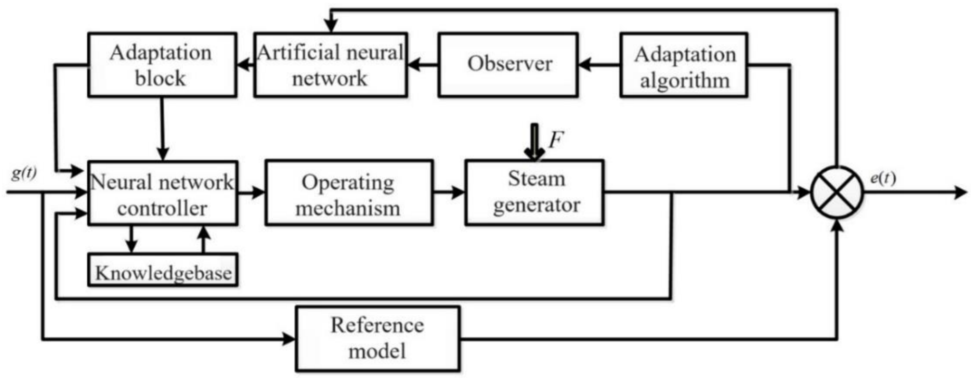

Fig. 1. ***Structural diagram of an adaptive fuzzy control system for steam generator temperature control.***

Here in the control loop is introduced a block of “adaptation algorithm” designed to evaluate and adjust the structure and parameters of the observer, as well as an adaptation block to adjust the nonlinear neuro-fuzzy controller.

One of the main tasks in the development of a neural-phase network based controller is the training of the network, as it significantly affects the accuracy and speed of calculation of control actions, i.e., the generation of fuzzy-logic output. This is directly related to the reduction of computational complexity, which leads to the simplification of software implementation of algorithms based on neural network and fuzzy logic [13].

This approach provides a number of additional advantages, such as operability of the system under conditions of incomplete initial information and the possibility of adjusting the regulator parameters in the process of system operation.

Currently, there are known approaches to the construction of fuzzy logic inference models based on the Mamdani and Takagi-Sugeno models [14]. At the same time for training fuzzy systems, as a rule, adaptive neuro-fuzzy inference systems (ANFIS - adaptive neuro-fuzzy inference system) [15] and hybrid technologies combining fuzzy models in the form of artificial neural networks [16], genetic algorithms [17] are used.

The high dimensionality of the analyzed object and the large number of input variables lead to an exponential increase in the number of fuzzy inference conclusions. This, in turn, decreases the accuracy of training fuzzy models.

The reason for this is that traditional fuzzy logic inference algorithms rely on rigid arithmetic operations, such as finding the minimum and maximum, which can be limiting.

Additionally, the accuracy of fuzzy logic models is affected by the architecture of the fuzzy rules and the chosen defuzzification method.

To overcome these drawbacks, the proposed approach uses soft arithmetic operations in fuzzy models to determine the minimum and maximum. This allows the control actions to be calculated while considering changes in the input parameters. Furthermore, the area difference method is used for training the neuro-fuzzy system.

It is important to note that the performance of the neuro-fuzzy network is significantly influenced by the form of the membership function (MF). In this paper, the relationship between input and output variables is formed using triangular membership functions based on fuzzy rules of the form:

$$Rule_i : If \;\; X_1 = x_{i1} \text{ and } X_2 = x_{i2} \text{ and} \ldots \text{and } X_n = x_{in} \text{ then } Y = y_i, \tag{1}$$

where X_n - input variable; n - number of input variables; x_{in} - linguistic term describing input MFs; i - number of terms y of input/output variable; Y - output variable; x_i - linguistic term describing output MFs.

The centre of gravity method can be used to calculate the resulting signal:

$$y_{defuz} = \frac{\int_{\min}^{\max} y \cdot \mu'(y) dy}{\int_{\min}^{\max} \mu'(y) dy},$$

where *min*, *max* - integration limits of the fuzzy set; $\mu'(y)$ - MF of the output variable after realisation on the basis of fuzzy rules of the fuzzy inference procedure.

Estimation of the fuzzy system is carried out by the criterion of standard deviation:

$$RMSE = \frac{1}{M}\sqrt{\sum_{i=1}^{n}\left(y_{dset} - y_{defuz}\right)^2} \rightarrow \min ,$$

where y_{dset} - set of trained data; M - number of points in the trained sample.

Soft arithmetic operations in fuzzy logic inference define the concepts of soft minimum and soft maximum. These operations provide a more gradual and flexible approach compared to the traditional minimum and maximum operations:

Soft minimum:

$$\min_{\delta} (x_1, x_2)_I = \frac{x_1 + x_2 + \delta^2 + \sqrt{(x_1 - x_2)^2 + \delta^2}}{2}.$$

Soft maximum:

$$soft-\max(x_1,x_2)=\left|\gamma\cdot\max(x_1,x_2)+0{,}5(1-\gamma)(x_1+x_2)\right|,\ where\ \ \gamma=0{,}7.$$

In the defuzzification process, the variables are calculated using the area difference method.

The training algorithm for the neuro-fuzzy system consists of the following steps, with the terms of the membership function represented by triangular or trapezoidal membership functions.

Triangular MFs

$$f(x;a,b,c)=\begin{cases}0,\ x\le a;\\ \dfrac{x-a}{b-a},\ a\le x\le b;\\ \dfrac{c-x}{c-b},\ b\le x\le c;\\ 0,\ c\le x.\end{cases}$$

Trapezoidal MF

$$f(x;a,b,c,d)=\begin{cases}0,\ x\le a;\\ \dfrac{x-a}{b-a},\ a\le x\le b;\\ 1,\ b\le x\le c;\\ \dfrac{d-x}{d-c},\ c\le x\le d;\\ 0,\ d\le x.\end{cases}$$

where a, b, c, d - parameters of the membership function; x - quantitative value of the input parameter having triangular form for the fuzzy system.

The neuro-fuzzy system under consideration has two input variables, $X_1=\{x_{11}\}+\{x_{12}\}+\{x_{13}\}$ and $X_2=\{x_{21}\}+\{x_{22}\}+\{x_{23}\}$, each with three terms, and one output variable, $y\in Y=\{y_1\}+\{y_2\}+\{y_3\}+\{y_4\}+\{y_5\}$, with five terms.

Step 1: Fuzzification operation of the input variables.

Step 2: Determination of the membership degree for each input information received.

Step 3: Synthesizing the knowledge base containing fuzzy rules as shown in Table 1.

Table 1

Fuzzy inference knowledge base

FR	If		Then	FR	If		Then	FR	If		Then
FR_1	x_{11}	x_{21}	y_5	FR_4	x_{11}	x_{21}	y_4	FR_4	x_{11}	x_{21}	y_3
FR_2	x_{11}	x_{22}	y_4	FR_5	x_{11}	x_{22}	y_3	FR_5	x_{11}	x_{22}	y_2
FR_3	x_{11}	x_{23}	y_3	FR_6	x_{11}	x_{23}	y_2	FR_6	x_{11}	x_{23}	y_1

The introduction of truncated membership functions ensures a rational positioning of the elements in the fuzzy relation matrix. As a result, the number of conclusions in the fuzzy inference is equal to the number of terms at the output membership function, which in this case is 6 (as shown in Table 1). In contrast, traditional fuzzy logic models would have a number of conclusions equal to the number of fuzzy rules, which would typically be between 9 and 15. Therefore, the proposed approach reduces the complexity of the fuzzy inference compared to traditional methods.

In Step 4, the defuzzification operation is carried out using the area difference method. In this case, the areas of the triangular or trapezoidal membership function terms are calculated using the following formula:

$$S=\frac{h}{6}(b_1+4b_2+b_3),$$

where h - height of the geometrical figure; b_1, b_2, b_3 - lengths of the lower, middle and upper bases of the geometrical figure.

Table 2

Matrix of fuzzy relations

Day off term	Composition			Maximum
y'_5	*b_1=soft-min(x_{11};x_{21})*	*b_5=soft-min(x_{12};x_{22})*		*b_1*
y'_4	*b_1=soft-min(x_{11};x_{21})*	*b_4=soft-min(x_{12};x_{21})*		*soft-max(b_2;b_4)*
y'_3	*b_1=soft-min(x_{11};x_{21})*	*b_5=soft-min(x_{12};x_{22})*	*b_7=soft-min(x_{13};x_{21})*	*soft-max(b_3;b_5;b_7)*
y'_2	*b_1=soft-min(x_{11};x_{21})*	*b_8=soft-min(x_{13};x_{22})*	*soft-max(b_2;b_4)*	*soft-max(b_6;b_8)*
y'_1	*b_1=soft-min(x_{11};x_{21})*			*b_9*

In Step 5: Network Acquisition, when training the neuro-fuzzy inference system, the standard ANFIS error backpropagation method can be utilized. However, in this specific case, the correction of the truncated areas of the output variable terms is performed until the output value y_{defuz} is as close as possible to the reference value, according to the following relation:

$$y_{out} = (w_i) + \delta(y_{defuz} - y_{etal}), \tag{2}$$

In the training step of the neuro-fuzzy inference system, the input value is denoted as δ, and the target output value is typically set to $\delta = 0{,}02$ by default.

The weight parameters of the neural network, denoted as w, are calculated using the standard ANFIS error propagation method. Based on this algorithm, the structural schematic of the ANFIS is developed, as shown in Fig. 2. This ANFIS structure consists of 9 layers.

Let us consider the operations performed on each layer:

In layer 1, a vector of input variables $U_{out} = f(x_1, x_2)$ obtained from the sensors of the control system is formed.

On layer 2, the phasification of input variables is carried out in the form of three parameterised terms $X_1 = \{x_{11}\} + \{x_{12}\} + \{x_{13}\}$ and $X_2 = \{x_{21}\} + \{x_{22}\} + \{x_{23}\}$, and the phasification of output variable of five parameterised terms: $Y = \{y_1\} + \{y_2\} + \{y_3\} + \{y_4\} + \{y_5\}$.

In layer 3, the calculation of b parameters of the fuzzy relationship matrix is carried out.

On the 4th layer the output parameters y'_i of the fuzzy relation matrix are calculated.

In Layer 5 of the ANFIS structure, the terms of the output variable are truncated based on the fuzzy rules, thereby determining the height of the membership function (MF).

In Layer 6 of the ANFIS structure, the weighting coefficients w of the neural network are formed by calculating the areas of the truncated terms of the output variable.

In Layer 7 of the ANFIS structure, the total area of the figure is calculated by summing the areas of the truncated terms of the output variable.

In Layer 8 of the ANFIS structure, the ratio of the total area to the area of the truncated terms of the output variable is calculated.

At the final layer (Layer 9) of the ANFIS structure, the neuro-fuzzy inference system is trained by minimizing the difference between the target value and the output variable's resulting value. This process is known as defuzzification, where the fuzzy output is converted into a crisp, numerical value.

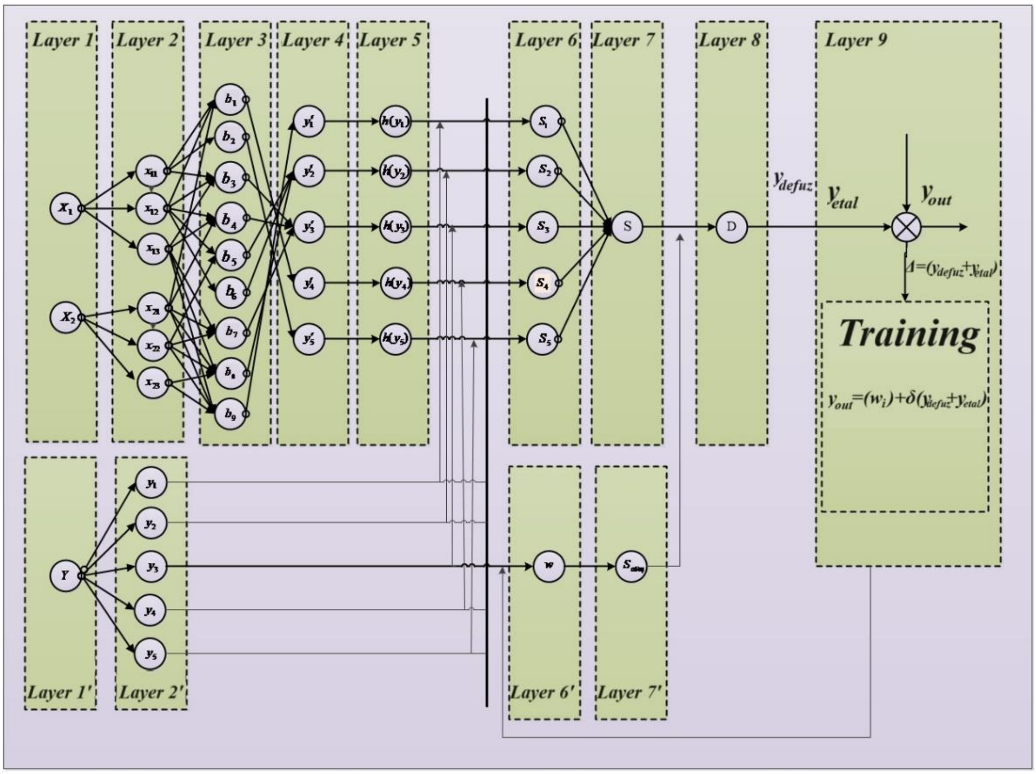

Fig. 2. ***The structure of an adaptive neuro-fuzzy inference system (ANFIS).***

The application of the soft arithmetic operations method in the training process has been shown to have an advantage over traditional training techniques.

It is also important to note that the proposed training method for fuzzy systems results in a response of the output variable across the entire domain of the input and output parameters.

Let us define the domain and range of the function within the interval [-1, 1]. In this case, the activation function has a fuzzy symmetric form about the origin and can be represented using a piecewise linear approximation. Under these conditions, the objective function to be minimized can be expressed as follows:

$$F(P) = \sum_{i=1}^{N} \left| y_i^* - y_i \right|,$$

where y and y^* - real and desired values of the object output, i - moment of time.

In order to investigate the dynamic properties of the steam generator, a number of computational experiments were carried out at different values of input influences. The input influences - fuel flow rate and cold temperature were varied by 7%, i.e., relative to the nominal one.

From the analysis of dynamic characteristics, we can conclude that the temperature of the steam generator is more sensitive to the change in fuel flow rate than to the change in its temperature. Thus, we choose fuel flow rate as the main controlling influence on the steam generator temperature regime.

The studies of this automatic control system have revealed that in the presence of external disturbances, such as a temperature change exceeding 15%, or parametric variations in the control object, like a 10% temperature change, the quality indicators of the transient response deteriorate significantly. In these situations of parameter changes, the control system can potentially enter an unstable state. This issue arises because in automatic control systems with fixed controller parameter values, the quality of the transient response varies depending on the disturbances and operating modes of the steam generator. The fixed controller parameters are not able to adequately compensate for the effects of these perturbations, leading to a degradation in the transient performance and potentially destabilizing the system. In other words, the control system with static controller parameters is not able to maintain the desired transient response characteristics when faced with external disturbances or internal parameter variations in the plant. This limitation of fixed-parameter control necessitates the need for a more adaptive, flexible control approach that can adjust to changing conditions and maintain stable, high-quality control.

The problem to be addressed is two-fold: to stabilize the controlled variable (steam generator temperature) with a desired level of transient response quality, despite having incomplete information about the control object; to obtain the properties of disturbance rejection and invariance to external perturbations in the automatic control system. In other words, the goal is to achieve stable control of the temperature variable while meeting the specified transient response requirements, even when the full details of the control plant are not known, and to ensure the control system is robust against external disturbances.

In this case, the control objective is to maintain the process parameter (steam generator temperature) within a specified range of deviations from the desired value, even in the presence of both controlled and uncontrolled disturbances. The key idea is that as the deviation of the process parameter from the target value increases, the increment that adjusts the controller's transfer coefficient should also become larger.

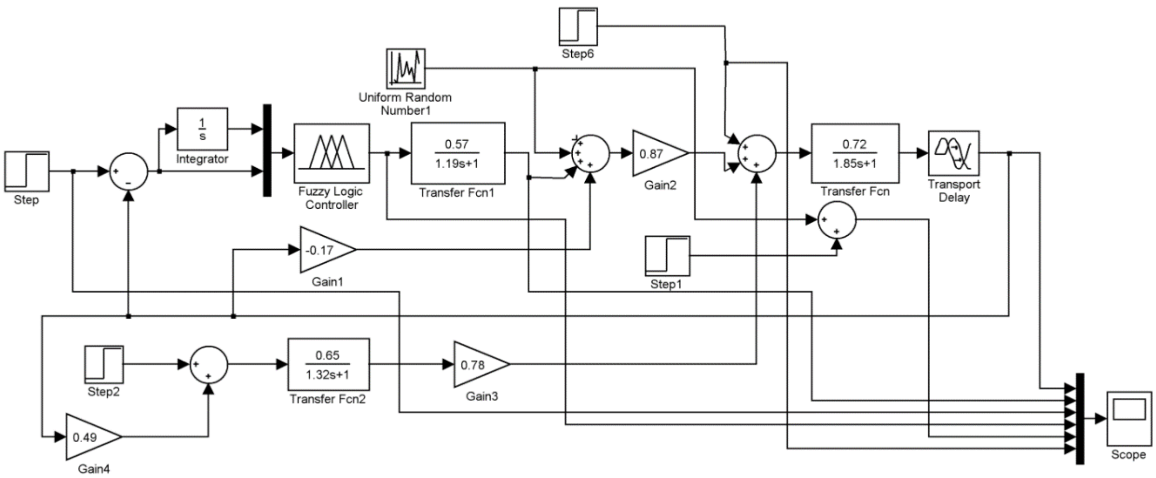

Fig. 3. ***Simulation model of adaptively fuzzy control system of steam generator temperature control.***

Based on these considerations, a simulation model of the fuzzy-based steam generator temperature control system was constructed in the MATLAB environment, as illustrated in Fig. 3. Using this model, a number of computational experiments were conducted in the presence of external disturbances and parametric uncertainties.

As a reference model, the transfer function corresponding to the actual state of the process will be utilized:

$$W(p)=\begin{bmatrix} \dfrac{5}{(p+10{,}96)(p+0{,}46)} & \dfrac{2{,}5}{(p+10{,}96)(p+0{,}46)} \\ \dfrac{0{,}28(p+12.50)}{(p+10)(p+0{,}5)} & \dfrac{10}{(p+10)(p+0{,}5)} \end{bmatrix}.$$

The computational experiment conducted in the Simulink MATLAB environment involved considering a step-like change in the temperature of the external environment (load), as depicted in Fig. 4.

The experimental results indicated that the optimal adaptation coefficient value is $y=0{,}65$. Fig. 5 presents a comparison of the performance between the adaptive-fuzzy system with a reference model using a constant adaptation coefficient (shown by the dashed line) and the adaptive system with a reference model that has a variable adaptation coefficient controlled by a trained artificial neural network (ANN). Additionally, Fig. 6 depicts the graph showing the variation of the adaptation coefficient (y) over the course of the transient process. This figure illustrates how the variable adaptation coefficient, as determined by the ANN, evolves dynamically during the transient response, in contrast to the fixed adaptation coefficient used in the first case. The comparison between the two approaches, as demonstrated by the results in Fig. 5 and 6, highlights the advantages of employing the variable adaptation coefficient controlled by the ANN reference model. This implementation leads to improved transient performance and enhanced control system stability compared to the fixed adaptation coefficient approach.

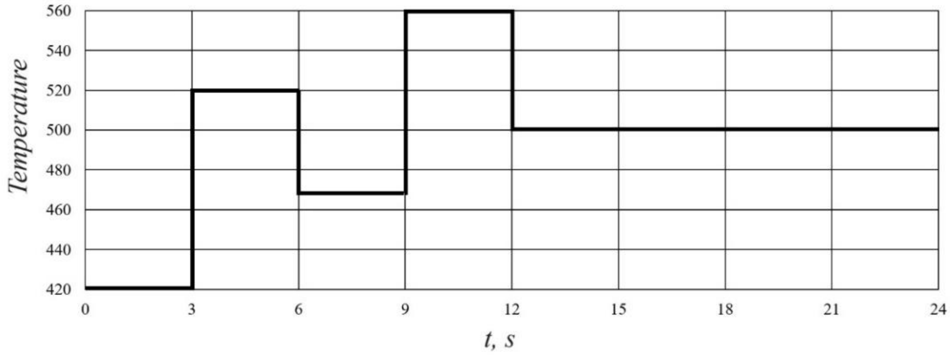

Fig. 4. ***Deviation from nominal temperature conditions.***

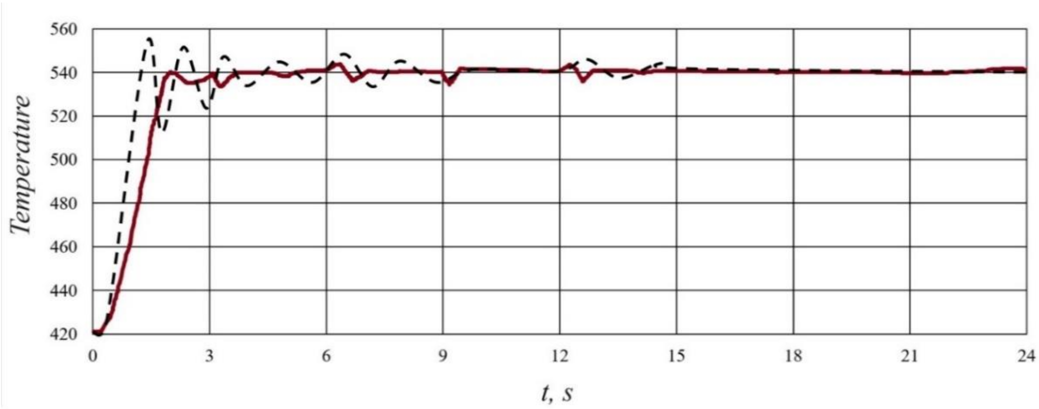

Fig. 5. ***Comparative transient response plots of the adaptive control system with a reference model: constant vs. variable adaptation coefficient.***

The obtained law of change of the adaptation coefficient is close to the relay law, which realises high speed of transients. Adaptive systems with a reference model are a widely used tool to improve the performance of control systems under uncertainty.

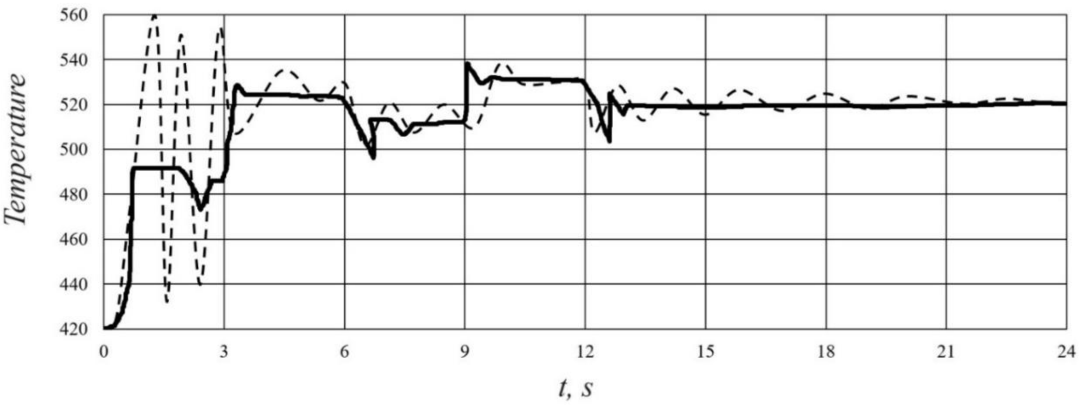

Fig. 6. ***Control signals during adaptation with constant and variable adaptation rate coefficient.***

The paper considers the modification of the adaptive-fuzzy system by incorporating a reference model. This implementation is achieved through a nonlinear control law that adjusts the adaptation rate coefficient y. The uniqueness of this approach lies in the fact that the parameters of the hidden layer activation functions and output layer weights in the adaptive-fuzzy system are made tunable. The experimental results demonstrate that controlling the adaptation rate coefficient of the adaptive-fuzzy system using a reference model implemented with a neural network leads to a significant improvement in the transient response quality. In other words, the incorporation of the reference model and the ability to tune the internal parameters of the adaptive-fuzzy system result in enhanced dynamic performance and faster convergence to the desired temperature control behavior, as evidenced by the improved transient characteristics.

The results of the computational experiments demonstrate that the developed controller endows the entire automatic control system with the ability to maintain the desired level of the technological parameter (temperature) even in the presence of external disturbances. Furthermore, the controller enables qualitative control of the temperature control process over a wide range of changes in its parameters over time. As shown in Fig. 6, the developed fuzzy controller confers the properties of parameter perturbation invariance to the overall control system. In other words, the control system exhibits robust performance and is able to effectively maintain the target temperature despite variations in the system parameters. The key takeaway is that the developed fuzzy controller, as part of the adaptive-fuzzy control system, provides the capability to reliably regulate the temperature, ensuring stability and consistency of the technological process, even in the face of disturbances and changes in the system's operating conditions.

Conclusion

This paper investigates the modeling and synthesis of an adaptive-fuzzy control system for steam generator temperature control. The aim was to develop a control system capable of providing high accuracy and stability of steam generator temperature control under diverse operating conditions. The paper proposes a synthesized system combining fuzzy logic and adaptation techniques to achieve more accurate and stable control of steam generator temperature. The detailed structural diagram of the system and the modeling and tuning methods are presented. The results of this study can be applied to enhance the efficiency and reliability of temperature control in steam generators across various industries such as power generation, chemicals, and manufacturing. Additionally, the paper reviews several key works on modeling and synthesis of adaptive-fuzzy temperature control systems for steam generators. The findings of these studies confirm the effectiveness and benefits of adaptive and fuzzy approaches in improving temperature control.

In summary, the development and application of a synthesized adaptive-fuzzy control system for steam generator temperature control has substantial practical significance. This approach can lead to improved control accuracy, stability, and efficiency over a wide range of operating conditions compared to conventional control methods. The key advantages of this synthesized system include: enhanced control performance through the integration of fuzzy logic and adaptive techniques; ability to handle the complex, nonlinear, and uncertain nature of steam generator systems; automatic adjustment of control parameters to cope with changing operating conditions; improved overall temperature control accuracy, stability, and responsiveness; further research and advancements in this area can make additional valuable contributions to the development of advanced control systems and the improvement of steam generator performance across various industrial applications, such as power generation, chemicals, and manufacturing.

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