Control on Temperature of Hybrid Nanofluid in Evacuated Tube Solar Collector Using Smart Curtain

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Abstract.
This research was revealed control on temperature hybrid nanofluid in evacuated tube solar collector system, where the hybrid nanofluid utilized as working fluid in ETC for enhancement the thermal performance for heating device. The smart curtain was used for purpose shadow the evacuated tube solar collector for controlling on temperature of the hybrid nanofluid in heating or cooling conditions. In addition, Adaptive neuro fuzzy inference system (ANFIS) a way of artificial intelligence was applied to control on the shadow the evacuated solar tube collector. Where the main principle of the curtain is to control the polarization of the sun radiation, the curtain work depends on three parameters were applied in ANFIS technique, two parameters are input variable like as (temperature of hybrid nanofluids (inlet, outlet) and ambient temperature, and one output parameter represents by (distance parameter).

Keywords— Adaptive Neuro Fuzzy Inference System, Fuzzy Logic Controller, Temperature of Hybrid Nanofluid.

1. Introduction
The future is the renewable energy. It protects the environment and enables more energy to be produced. Solar power is a significant form of power. Currently, solar collectors like flat panel, evacuated tube, parabolic trough, dish collectors are used to collect heat from solar energy [1, 2, 3]. Hybrid nanoparticles are the most desirable means of improving the efficiency of heat transfer devices. The hybrid nanofluid is composed of mixing hybrid nanoparticles with the working fluid [4, 5, 6, 7, 8, 9]. Adaptive network-based fuzzy inference system is an adaptive network that enables the implementation of neural network topology in conjunction with fuzzy logic.

ANFIS system involves elements of the traditional fuzzy system, Also the calculation on each level was executed by a layer of hidden neurons and the learning capacity of the neural network is provided to improve system knowledge. ANFIS is able to handle complicated, non-linear, dynamic systems in additional it implements a Takagi-Sugeno fuzzy inference system [10] and has a five-layered. Analyzing the mapping relationship between the input and output data. ANFIS can determine the ideal distribution of membership functions using either a back-propagation algorithm by itself or in combined with a least-square technique similar to ANNs. ANFIS network is trained based on experience of supervisor learning to achieve a specific target output from a particular input. Jang initially introduced the ANFIS methodology in the early 1990 [11], its applications to the modeling of thermal energy systems is somewhat recent. Several studies using ANFIS for modeling, control, performance prediction in energy systems [12, 13, 14, 15].
2. Neuro-Fuzzy system Layers (ANFIS Architecture)

Hybrid (ANFIS) is one of the Artificial Intelligence methods that belong to one of the adaptive networks, functionally equivalent to the fuzzy systems. It is assumed that there are two inputs x, y and output z in the fuzzy inference system. According to figure(1) ANFIS implements a fuzzy inference system from Takagi Sugeno [11] and has five layers as shown in Figure 1 Sugeno fuzzy model has the following rules of first order as follows:

Rule 1: If x is $A_1$ and y is $B_1$ Then $F1= P_1 x + q_2 y + r_1$

Rule 2: If x is $A_2$ and y is $B_2$ Then $F2= P_2 x + q_2 y + r_2$

Layer 1: Fuzzification layer each node in layer 1 is a node-function adaptive node. Parameters in this layer: parameters of the premise (or precedent).

\[ O_{1,i} = \mu_{A_i}(x) \quad i = 1, 2 \]

\[ O_{1,i} = \mu_{B_i-2}(x) \quad i = 3, 4 \]

\[ \mu_A(x) = \frac{1}{1 + [(x-c_i)^2/a_i^2]^{b_i}} \]

Where: $\mu_A(x)$ and $\mu_{B_i-2}$ are the membership function levels for the fuzzy sets $A_i$ and $B_i$, respectively, and $(a_i, b_i, c_i)$ are the membership function parameters that can change the membership function shape.

Layer 2: rule layer is a fixed node marked () with the output of which all incoming signals are produced:

\[ O_{2,i} = w_i = \mu_{A_i}(x) \times \mu_{B_i}(x) \quad i = 1, 2 \]

Layer 3: normalization layer, the nodes of which are labelled N. Its function in the following process is to normalize the weight function:

\[ O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2} \quad i = 1, 2 \]

Layer 4: defuzzification layer with adaptive nodes. The output equation is w $\overline{f_i} = \overline{w_i}(p_i x + q_i y + r_i)$

Where: $\overline{w_i}$ is the normalized firing strength from layer 3, and $(p_i, q_i, r_i)$ are the consequent variables set of the node.

Layer 5: summation neuron the single node in this layer is a fixed node labelled 5,1 (overall output), which computes the overall output as the aggregation of all incoming signals

\[ O_{5,1} = \text{overall output} = \sum \overline{w_i} f_i \]

When premise parameters are fixed:

\[ F = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 = \overline{w_1} f_1 + \overline{w_2} f_2 \]

Which is linear in the consequent parameters $(p_1, q_1, r_1$ and $p_2, q_2, r_2)$.\[ ]
3. Evacuated tube solar collector with shadow system

In this work was added a shadow system to the ETCS in order to contribute to the development of the system performance of the solar heater and the control of the temperature of the fluid hybrid as shown in Figure 2 and 3. The curtain contributes to covering the solar heater system where it works for controlling the temperature of the hybrid nanofluid present in the heater. The curtain moves up and down by mechanical and electrical parts depending on the set conditions that control the movement. This curtain is made of (Flex) white rubber material and is considered one of the strongest printing materials because it is characterized by resistance to tension, pressure and weather. Figure 4 and 5 illustrate the curtain which is mounted on frame and the ETC with shadow system.

Figure 2. Schematic diagram of the ETSC with shadow system.

Figure 3. The solar heating system used in the experiments with shadow system.
4. Components used in shadow the solar collectors

Here we explain the hardware equipment response on movement the curtain. The curtain system consists of a mechanical part and an electrical part. Where a mechanical part consists of the outer frame base is made of metal iron, as show in Figure 6 the goal of this framework is the installation of curtain, stepper motor and shift. From another hand the electrical part consists of a stepper motor and a power supply in addition microcontroller (arduino). In Figure 7 show the control board involve the electrical part. It has also been linked to some sensors such as temperature sensors (thermocouple sensor) as well as sensors for distance (ultra sonic) to the control circuit Figure 8 and 9.

Figure 4. The mounted curtain on frame.

Figure 5. ETC with shadow system.

Figure 6. The mainframe with curtain.
5. Design the sugeno fuzzy rules by using ANFIS

Fuzzy logic tries to simulate our decision-making and is capable of providing precision findings depending on unknown and indefinite information. Mamdani and Sugeno were most popular fuzzy inference designs. Usually both designs may be described as (if the antecedent is the consequence) to all fuzzy designs, the antecedence is the same, But the result of each template has distinct types. At Sugeno fuzzy design two factors are regarded as fuzzy inputs such as $T_{hf}$ and $T_a$. A typical Sugeno fuzzy rule in the proposed ANFIS model with two inputs $T_{hf}$ and $T_a$, and one output Dist. can be shown as $\text{If } T_{hf} = x \text{ and } T_a = y, \text{ then } \text{Dist.} = f(T_{hf}, T_a)$, where $x$ and $y$ are the membership function of data entered $T_{hf}$ and $T_a$, respectively.

At Sugeno fuzzy design, $f$ is a crisp function, frequently a linear input factor feature as:

$$f(T_{hf}, T_a) = pT_{hf} + qT_a + r$$  \hspace{1cm} (1)

The suggested classification of ANFIS, as shown in Figure 10, involves three main components: Fuzzification, Sugeno Fuzzy Inference Engine, and Defuzzification. As noted above, for each sample
n, two input variables: Thf and Ta are considered. ANFIS goal is to calculate the distance for each sample n, Dist. (n), according to data entered. Fuzzifier switching the normalized inputs to linguistic fuzzy parameters utilizing the membership functions. The membership functions for data entered could be viewed in Figure 11 The fuzzy sets employed to fuzzy of Each entry parameter that can be categorized into three membership features: (Low, Medium and High).

Figure 10. Suggested classification of ANFIS.

Figure 11. Two inputs of memberships function.

According to the range of the data entry for the sample n, several of the fuzzy rules will fire. Then, weighted average defuzzification method was applied to create the final crisp output Dist(n) from the aggregation of the fired outputs \( \text{out}_k(n), k=1,2,\ldots,9 \) depend on Equation 2, in which, \( w_k \) is the minimum of the memberships of the data entered \( T_{hf} \) and \( T_a \) within the Rule \( k \) of Equation 2.

\[
\text{Dist}(n) = \frac{\sum_{k=1}^{9} (w_k \times \text{out}_k)}{\sum_{k=1}^{9} w_k}
\]  

(2)

In fuzzy system, the number of fuzzy memberships for every data entry is 3 (Low, Medium, and High). Therefore, the number of fuzzy if-then rules is \( 3^3 = 9 \), where every rule own 3 constant variables \( (p_k, q_k \text{ and } r_k) \). Hence, the total amount of Manageable variables in the fuzzy system is \( 3 \times 9 = 27 \). This is a Sugeno fuzzy design for stepping motor control. We apply the technique of ANFIS to predict the membership function factors and the resulting functions. Of each linguistic variable, we utilized a fuzzy design of 9 rules and 3 membership functions.

6. ANFIS editor

The ANFIS Editor contains on fuzzy tool box can be utilize it for generate constructing, and optimizing Sugeno-types adaptive neural fuzzy inference systems. The following Figure 12 Showed the name of each input factor on the left and the output on the right. Figure 13 Shows ANFIS models structure was developed with 2 inputs, 1 output and 9 fuzzy rules. Figure 14 Revealed the relationship between the
error and number of epoch. From another hand, the Rule Editor allows automatic construction of the rule sentence as indicated in the FIS Editor by to the description of the input and output factor specific with the FIS Editor. As shown in Figure 15, in addition the Rule Viewer shown in Figure 16 Displays a road map of the whole fuzzy inference process. Furthermore the Surface Viewer shown in Figure 17 with two-input one-output schemes as can generate three-dimensional charts that MATLAB can adjust to manage.

**Figure 12.** Input/Output membership function.

**Figure 13.** ANFIS structure.

**Figure 14.** (FIS) editor.
7. Simulation Results
After obtaining the standard real data of parameters such as (temperature of hybrid nanofluids, ambient of temperature and distance) from the solar collector. Adaptive Neuro-Fuzzy Inference System (ANFIS) method was utilized for forecasting the output of distance of electrical curtain. After completing the training process for Multifunction’s (Triangular - Gaussian - Bell - Trapezoidal) was applied for training the parameters findings show best linear functions were obtained by the number of epoch and number of the layer. Table 1 shows the Training Error of the (inlet and outlet) Temperature hybrid nanofluids with shadow in ETC.

Figure 18 explain the stepping motor reaction to a sequence of step input signals. We show in Figure 19 the findings of the application of the ANFIS procedure with test data (240 samples were used). The
Table 1. Training Error of the (inlet and outlet) Temperature hybrid nanofluids with shadow in ETC

| Multifunction's Type | No. of Layers | No. of Iterations | Average Error |
|----------------------|---------------|-------------------|---------------|
| Constant             | 6             | 40                | 0.00227698    |
| Triangular           | 6             | 40                | 0.00227093    |
| Trapezoidal          | 6             | 40                | 0.00228354    |
| Bell shapped         | 6             | 40                | 0.00225577    |
| Symmetric Gaussian function | 6     | 40                | 0.0022612     |
| Linear               | 6             | 40                | 0.00222149    |
| Triangular           | 6             | 40                | 0.00237731    |
| Trapezoidal          | 6             | 40                | 0.0022579     |
| Bell shapped         | 6             | 40                | 0.0022612     |
| Symmetric Gaussian function | 6     | 40                |               |

Training error was explained in Figures 20. In the process of shading the ETC collector the electric curtain starts to work based on the temperature of the hybrid nanofluid, where the maximum height of the curtain is approximately 140 centimeters when the nanofluid temperature is 90°C. The curtain is in a fully open state at low temperatures around 5°C, at various mass flow rate and volume concentration.

Figure 18. Response of the stepping motor to a sequence of step input signals.
Figure 19. Findings of applying the ANFIS methodology.

Figure 20. Training Error and Training data with FIS.

8. Conclusion
(i) ANFIS technique was for forecasting the output distance parameter of the smart curtain.
(ii) ANFIS a technique is applied to designing the fuzzy rule base of the smart system into control. In specific.
(iii) The ANFIS approach has been applied to construct a Sugeno fuzzy model to regulate the stepper motor drive.
(iv) The role of the electric curtain is to control the temperature of the hybrid fluid and increase the efficiency of the ETC.

(v) Applying ANFIS method for simulating the ETC parameter and evaluated the performance of these parameters.

(vi) ANFIS is a perfect option for realizing the desirable precision and efficiency in controlling stepping motor.

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