Estimating the Temperature of the Outlet Water of Cooling System of Gas Turbine V94.2 Using Fuzzy Neural Network

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Abstract—Heat transducers are one of the basic parts of heating and cooling systems. Various types of such transducers are used in powerhouse industries. In this article we try to study the functions of a heat-air-water transducer used in the cooling system of gas-turbine. As there is not enough information about the structure and components of such transducers, we have estimated the output temperature of this transducer by using other effective factors’ fuzzy neural method in the system.

Keywords— Fuzzy Neural Network, Gas-Turbine V94.2, Heat transducer, Temperature estimation.

I. INTRODUCTION

Heat transducers are almost the most useful devices in industrial units. Such transducers make it possible to transfer heat energy between two or several fluids at different temperatures. This action can be done between liquid-liquid, gas-gas, or gas-liquid in order to cool hot fluid or heat it. Heat transducers have a wide range use in powerhouses, refineries, petrochemical industries, heating, air conditioning, refrigeration systems, etc. The radiator in a vehicle is a simple example that has the duty of cooling the engine oil, and also, in powerhouses, they cool the different parts of the machinery. Heat transducers can be classified in different viewpoints according to the type and level of contact, the direction of fluid flow, heat transfer mechanism, and its mechanical structure [1].

Using modeling, we can evaluate the efficiency of the system. Some factors like sedimentation in the internal parts, variation in the system operating point during the time and etc. reduce the system efficiency. For instance, adding more additives to the cooling fluid than necessary or changing their ratio, reduces the heat capacity in the transducers; as a result, their efficiency reduces.

There are two general methods of modeling for a system [2]. They are modeling through math rules and identification through parametric and non-parametric methods.

Math modeling is highly complicated and difficult. Although these methods are efficient, determining the coefficient of the model according to algebra is difficult and time-consuming. Not having enough and thorough information about the features of the system and their changes during the time and also the present uncertainties reduce the accuracy of these models during the time and change the coefficients of the model. Hence, the models should be modified according to the system changes. While there is not enough and thorough information about the system to the extent that creating a model for the system is impossible through math rules, parametric and non-parametric methods are used for determination. Such method views the system as a black box or grey box having several in-lets and out-lets.

In some papers, heat transducer modeling and cooling systems through math rules and the equations controlling the system have been studied. In [3-4], the function of the cooling towers has been studied and a math model has been presented for it. In [5], a math model for pipe and crust heat transducers is presented. Other actions have been taken in this field [6-7] each having its own complications. Most of modeling methods used for heat transducer rate are focused on estimation of the heat transfer used for designing such a system.

Using neural nets in simulation area and day-to-day control is gaining popularity. Since the neural system needs no information about system or process, this method acts as a black box. Estimating response of physical systems containing complicated equations has been greatly simplified by neural net. Neural nets have been used for heat transducer behavior modeling in the two forms of static and dynamic. In [8-11] such transducer’s dynamic behavior has been studied in terms of functions like cooling and air conditioning. In [12], a heat transducer behavior has been evaluated dynamically. In [13], a dynamic neural net has been used to study the function of a heat transducer in an air conditioning system. Moreover, neural nets have been used in controlling the systems using heat transducers. In [12], the controlling of output air temperature has been done by using air flow speed change by a controller presented based on IMC and by using neural net.

In this paper, we will study temperature estimation in an air-water heat transducer, which is a fine tube used in the gas turbine water cooling system. This type of transducer has four forced draft, which pipes are covered with...
transverse blade on the outside layer. The mentioned blades are used to increase the heat transfer coefficient.

The paper structure is as follows: First, we will describe the heat transducer and cooling system in a gas powerhouse. In the third part, a brief introduction to system identification and present models of identification is presented. Later on, by describing a Neural Fuzzy Structure, a model for estimating the output water temperature from the heat transducer is inferred, and it will be evaluated and examined in this model. The last section concludes this paper.

II. SYSTEM DESCRIPTION

Water cooling system in the V94.2 gas units is a closed circuit and is divided into two basic parts. One group includes generator heat transducers, and the lubrication system inside the turbine structure and the second group includes pumps, air-water heat transducer, surge tank and fans located in outside of the turbine structure and outdoors.

Working Pressure 2.9bar  
System Operating Point Temperature 28°C  
Fluid Flow 410m³/h  
Fluid Speed (water) 2m/s

The inlets considered for the heat transducer modeling are: temperature of water entering transducer, the environment temperature, the amount of air flow on the transducer and the amount of fluid flow, which is water. The system acts as a closed cycle, so the amount of the fluid flow is stable in the transducer. As the number of fans is fixed in the system, we have considered that the amount of the air flow produced by them is fixed. Hence, the system has two inlets and one outlet. The main inlet of the system is input water temperature to the heat transducer, and the second inlet is the environment temperature. The environment air temperature can be measured as a turbulence in the system. The system outlet is the temperature of water leaving the air-water heat transducer.

III. AN INTRODUCTION TO SYSTEM IDENTIFICATION

The system identification is the best way to extract system’s features from the measured data. Identification refers to modeling dynamic systems by using observations and previously gathered data [15].

As mentioned before, there are two basic methods of presenting a model for the system.

- Modeling by math rules.
- Modeling by parametric and non-parametric methods.

Non-parametric are methods that stroke response is directly created without considering a specific model. Transient analysis is one of these methods that is based on the system response to step input or stroke. Transient analysis is not used for the exact estimation of the system; it is used for estimating the delay, and the time constant of the system [16]. Another non-parametric method is modeling by Fuzzy or Neural nets. ARX and position space belong to the group of parametric methods.

Choosing the model structure is one of the most important parts of modeling a dynamic system. Other efforts in modeling are highly dependent on a proper choice in this phase and any flaw in this phase can be Irrecoverable. In modeling it is important to have an exact model as much as possible and to be properly used in designing a controller.

Hence, despite the high accuracy in describing the features of the system, most of the complicated models cannot be used due to the existing limitations. The models presented for dynamic systems generally have two basic structures [17]: predicting structure and simulation structure. In predicting structure, the future output of the system is estimated according to past input and output of the system. Among different existing models based on predicting structure, the ARX, and AR can be mentioned for linear cases, and NARX and NAR can be named for nonlinear cases.

In simulation structure, the system future outputs are solely determined according to the past inputs. BJ and OE models are examples of this structure.
IV. NEURAL FUZZY NETWORK (ANFIS)

In this part, a complete algorithm is presented to solve the fuzzy relational equations in order to interpret the deduction rules in developing fuzzy propositional logic. This algorithm is made through a combinational neural architecture shown in fig. 2.

A. Neural fuzzy net

We suppose that $Y = \{y_1, y_2, y_3, ..., y_n\}$ is a defined fuzzy set on the propositions of output set. In fact, any $y_i$ shows an $i$th degree output fuzzy proposition which is satisfied. The neural fuzzy net input is also defined as a fuzzy set $X = \{x_1, x_2, x_3, ..., x_n\}$ on propositions input set. Every $x_i$ shows the $i$th degree of revealed input proposition [18].

![Fig.2. Neural fuzzy architecture](image)

This net is suggested as: $X \rightarrow Y$, which is the system knowledge in a neural fuzzy structure. After evaluating the input propositions, some output propositions presented in the system knowledge can be identified with the help of fuzzy system reasoning. One of the frequently used methods of fuzzy deduction systems is approximate reasoning, which could be done based on combining deduction rules [18]. The classes of T-norm have been studied by different researchers (Hirota&Pedrycz, 1996; Jenei, 1998; Lin and Lee, 1995). The following equation can be defined by using $\omega_t$ as follows.

$$ w_t(a, b) = \sup\{x \in [0,1] | t(a, x) \leq b \} $$

Then by adding the following two function $\tilde{\omega}, \tilde{\omega}_t: [0,1] \times [0,1] \rightarrow [0,1]$, which are defined by applying the following equation

$$ \tilde{\omega}_t(a, b) = \{ \begin{array}{ll} 1 & a < b \\ \alpha \vee b & a \geq b \end{array} \} $$

$$ \tilde{\omega}_t(a, b) = \{ \begin{array}{ll} 1 & a < b \\ \alpha \wedge b & a \geq b \end{array} \} $$

In which

$$ \alpha \vee b = \sup\{x \in [0,1] | t(a, x) = b \} $$

$$ \alpha \wedge b = \inf\{x \in [0,1] | t(a, x) = b \} $$

by applying mentioned operators, combination of fuzzy relations can be defined. Such combinations are used in creating fuzzy relational equations and showing symbolic knowledge based on rule by taking advantage of fuzzy deduction (Stamou & Tzafestas, 2000). $X, Y$ and $Z$ are considered to be three crisp sets with cardinality of $n, l, m$ respectively and $A(X, Z)$ and $B(Z, Y)$ are two fuzzy binary relations. The combinations $\sup - t$ and $\inf - w_t$ are assumed as following:

$$ (A^{\vee t}B)(i, j) = \sup_{k \in N_l} t(A(i, k), B(k, j)), \quad i \in N_n, j \in N_m $$

$$ (A^{\wedge \omega_t}B)(i, j) = \inf_{k \in N_l} \tilde{\omega}_t(A(i, k), B(k, j)), \quad i \in N_n, j \in N_m $$

Now we will explain the neural fuzzy architecture recommended in fig. 2 in more details. This architecture is composed of two layers of combinational neurons. The operation of normal neurons is described by the following equation:

$$ y = a' \left\{ \begin{array}{ll} \sup & \text{if} \quad \omega_t \end{array} \right\} $$

In which $t$ is a soft - $t$ and $a'$ is an activation function as follows:

$$ a' = \{ \begin{array}{ll} 0 & x \in (-\infty, 0) \\ x & x \in [0,1] \\ 1 & x \in (0, +\infty) \end{array} \} $$

The second type of combinational neuron is made by $\tilde{\omega}_t$ operation. The neuron equation is determined as follows

$$ y = a' \left\{ \inf_{i \in N_n} \tilde{\omega}_t(A(i, j), B(k, j)) \right\} $$

The recommended architecture is a two-layer neural net of combinational neurons shown in fig. 3. The first layer contains $\inf - w_t$ neurons, and the second one contains $\sup - t$ neurons. The system takes the propositions as input and the identified proposition output as output. The first layer calculates the rules mapping, while the second layer does the fuzzy reasoning by fuzzy modus ponens model. Rules have been used for the fuzzy neural net initialization. During the training, some of the neurons are in the hidden layer, and the weights may change by training in order to minimize the defects. The teaching algorithm that supports the above net is independently used in each layer. After the training process, the net preserves the created structure and the presented new knowledge can be extracted from if-then rules mapping [18].

B. Model validation

The ANFIS program in the software MATLAB has been used to test the program. In this method, first we applied 20000 data to fuzzy neural net for training. Membership function for the input was considered as trimf, and seven membership functions were hired for each input. The neural fuzzy system response to the training data is shown in fig. 4.
In fig. 4, the blue curve is the real output of the cooling system and the red curve is the ANFIS output. As shown in the following picture, the ANFIS output response properly follows the system response. The ANFIS model structure is shown in fig. 5.

V. MODEL VERIFICATION

In this section, we applied 10000 new data sampled from the system to the previous neural fuzzy net in order to verify the neural fuzzy net. The neural fuzzy net response for this case is shown in fig. 6, the accuracy of the neural fuzzy net in estimating the cooling system output temperature can be clearly observed.

VI. CONCLUSION

The water cooling system in gas units plays a significant role in proper usage of generator and turbo compressor. In this article, one of the parts of this cooling system namely air-water heat transducer was studied. The water temperature leaving the pumps was estimated by ANFIS neural fuzzy net. The comparison between the real and simulated data in the system showed that the model output followed the water temperature leaving the pumps with a good accuracy.

REFERENCES
