Development of a Parameter-Based Control System using Neural-Fuzzy Approach

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Abstract
The capabilities of the two computational intelligence technologies including neural network and fuzzy logic can be synergized through the formation of an integrated and unified model which capitalizes on the benefits and concurrently offsets the flaws of the involved technologies. In this paper, a neural-fuzzy model, which is characterized by its ability to suggest the appropriate change of process parameters in a relatively complex parameter-based control situation involving multiple parameters, is presented. This model is particularly useful in multiple input and multiple output situations where complex mathematical calculations are required if conventional control approach is adopted. In particular, it serves to acquire knowledge from the information base for extracting rules which are then fuzzified based on fuzzy principle. To validate the feasibility of this approach, a test has been conducted based on the neural-fuzzy model with the objective to achieve heat transfer enhancement in rectangular ducts using transverse ribs. This paper describes the roadmap for the deployment of this hybrid model to enhance machine intelligence of a complex system with the description of a case study to exemplify its underlying principles.

Keywords
Machine Intelligence, Neural Network, Fuzzy Logic, Heat Transfer.

INTRODUCTION
In industrial and engineering applications, parameter-based control systems are normally employed in situations where parameters such as heating temperature, injection pressure and cooling time need to be adjusted to achieve the required outcome of the overall condition. Traditionally, Proportional-Integral-Derivative (PID) control algorithms are adopted to deal with these parameter-based control situations albeit complex mathematical equations need to be used to analyze the operating conditions. However, the mathematical analysis based on relevant algorithms may become more complex when dealing with Multiple-Input Multiple-Output (MIMO) control situations where more than one input is used with more than one output. A typical example of MIMO is the control of flow rate (e.g. gallons/hour) and temperature (e.g. degrees C) of a certain liquid (e.g. water) by adjusting the hot tap and the cold tap of that particular liquid (in this case it is water) for a specific industrial or engineering process. The complexity of this type of control (two inputs and two outputs) is that a slight change of either one of the taps (hot or cold) affects both the temperature and flow rate of the output liquid. The mathematical equations involved in the PID control algorithms of such a MIMO situation are rather complex. By the same token, the level of complexity can be visualized if more than two inputs and two outputs are involved, noticing that this is not uncommon in actual engineering processes and operations. The analysis of MIMO control using PID algorithms can be found in a number of publications (such as Driankov et al [1]) and therefore not to be covered in this paper.

To address this MIMO situation, a model incorporating computational intelligence technologies such as fuzzy logic, neural network and genetic algorithms, can be employed. It is known that a system with the inclusion of the artificial intelligence elements is able to enhance the performance, reliability and robustness of control by incorporating knowledge which cannot be accommodated in the analytic model upon which the design of the control algorithm is based [1]. This paper presents a neural-fuzzy model, which is featured by its ability to recommend the adjustment of process parameters in a MIMO parameter-based control situation involving multiple parameters. This model is particularly useful in situations where complex mathematical calculations are required if conventional control algorithm is adopted. In particular, it serves to acquire knowledge from the information base for extracting rules which are then fuzzified based on fuzzy principle. A case study has been conducted related to the heat transfer situation where multiple parameters, such as rate of radiation and rate of conduction, are involved. Most importantly, this paper outlines the roadmap for the deployment of this hybrid model to deal with complex control situations in various engineering and industrial applications.

THE NEURAL-FUZZY MODEL WITH PRACTICAL EXAMPLE
The neural-fuzzy model proposed in this article is focused on the approach to find the required results without involving too many mathematical calculations. To exemplify the procedures and steps of this non-mathematical approach, a

practical example is employed to illustrate how it can be used to deal with a real life MIMO problem.

Description of the case

An overview of the thermal system under test is shown in Figure 1. The main portion to be discussed in this paper is the "Test Section" of the system, which is further explained in Figure 2.

In the present study, experiments are conducted for six repeated ribs to investigate the overall heat transfer from the tip portion as well as the sides of the ribs. The experimental apparatus was a long rectangular duct of 1.22 m length, with the test section at 50 cm from the inlet. The cross sectional area of the test section was 190(W) x 170(H) cm^2. The test geometry comprised six rectangular aluminum ribs of various cross sections and 190 cm long. A suction fan with variable speed control was connected to the exit of the duct. A 13mm thick aluminum plate was placed on the bottom of the duct and it was heated with an electric heater (input power rating: 1000W). The backside of the heater was insulated with glass wool to minimize the heat losses. Mica and insulation wood were used to insulate the aluminum and electric heater to avoid short circuit. The electric heater was controlled by means of a variable transformer. K-type thermocouples (1-mm diameter) were used to detect the temperature at the top and sides of each rib by inserting them in a small groove along the top surface and the upstream and downstream sides. These thermocouples were connected to a thermocouple scanner for simultaneous temperature measurements. An XYZ table was used to maintain the instruments in the correct position.

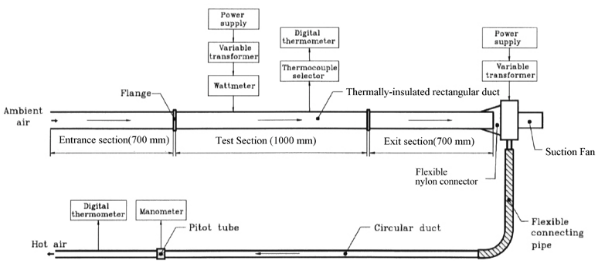

Figure 1. An overview of the thermal system under test showing the heat transfer process within the system of the case.

The geometry of the rectangular duct with transverse ribs of equal spacing is illustrated in Figure 2. The following additional assumptions are also made:

- Laminar flow
- Newtonian and incompressible fluid
- Constant fluid properties
- Steady-state

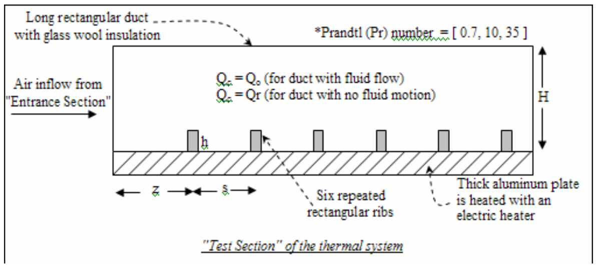

Figure 2. Side view of the long rectangular duct with transverse ribs of equal spacing, showing all the essential parameters for heat transfer study within the "Test Section" of the thermal system.

The air velocity inside the duct was maintained at 9.75 m/s. The average room temperature and pressure were 22 ^{o}C and 757 mm respectively. Measurements of rib temperature were taken an hour after the commencement of each experiment to allow for stability of readings. It can be seen that for each experimental investigation a new aluminum plate of different rib dimensions and spacing would be required.

A rib zone is defined as the area along the contour of the ribs and inner duct surface between the midpoints on the tips of adjacent ribs. The first rib zone is the area from the inlet of the duct to the midpoint on the tip of the first rib. The last rib zone is the area from the midpoint on the tip of the last rib to the exit of the test section. The values of Q/Qo are relative measures of performance representing the ratio of heat transfer from the inner wall for a rib zone to the heat transfer from the corresponding zone on an unribbed duct. The values for Q/Qr represent the amount of heat conducted from the zonal area to outer wall of an otherwise unribbed duct with no airflow.

The steady-state convection heat transfer, Q, from the rib surfaces to the fluid flow was deduced from the input power (E) as follows:

$$Q_c = E - Q_{rad} - Q_l \qquad (1)$$

Where Q_{rad} = the rate of radiation loss through both ends of the duct to its environment and it can be estimated by means of the following equation i.e.

$$Q_{rad} = \varepsilon\sigma(Tc^4 - Ta^4) \qquad (2)$$

Where	ε	=	emissivity of duct surface
	σ	=	Stefan-Boltzmann constant (W/m^2-°K)
	Tc	=	Average rib side temperature (°K)
	Ta	=	Average air temperature measured upstream of the test section (°K)

And	Q_l	=	the rate of conduction heat loss through the external surface of the rectangular duct assembly to the surroundings and it can be estimated by using the Fourier's Law, i.e.

$$Q_l = kA(Tc - To)/L \quad (3)$$

Where	k	=	thermal conductivity of duct material
	A	=	internal surface area of duct
	To	=	ambient air temperature
	L	=	thickness of duct

Hence in the case of a ribbed duct with fluid flow, Q_c = Q; whereas in the case of an unribbed duct, Q_c = Qo (for duct with fluid flow) and Q_c = Qr (for duct with no fluid motion). The Prandtl (Pr) number is a dimensionless quantity depends solely on the physical properties of the fluid, irrespective of flow conditions.

METHODOLOGY FOR DESIGNING A NEURAL-FUZZY MODEL

As depicted in the above context, the two different values (Q/Qo and Q/Qr) are the outputs affected by the four input parameters (Pr, z/H, s/H and h/H). The dimensions of ribs and their spacing (i.e. z/H, s/H and h/H) depend mainly on the magnitude of the overall heat transfer. This is considered to be a parameter-based control situation where complex mathematical analysis is required if conventional control theory is used. The proposed neural-fuzzy model consists of a neural network for acquiring the knowledge between the input and output data, and a fuzzy logic reasoning mechanism for generating a more reliable suggestion for modifying the induced output values from the trained neural network.

A methodology with a step-by-step approach has been developed for those who would like to tackle a MIMO parameter-based control problem using a hybrid neural-fuzzy approach which is able to significantly simplify the tedious analytical work of a conventional PID approach. In particular, this proposed hybrid approach does not require the prior knowledge of the theoretical aspects of neural network and fuzzy logic and therefore is meant to be used by novice users. The following steps provide guidelines for the development of such model.

Step 1 - Determine the input and output parameters of the neural network

The first step of the methodology is to determine the input and output values of the neural network with the purpose to obtain data for training purpose. The two key parameters of heat transfer are Q/Qo and Q/Qr with required performance as shown in Table 1:

Table 1. The two key parameters of the heat transfer model (Q/Qo and Q/Qr)

	Q/Qo	Q/Qr
Experimental heat transfer ratio	1.4698	5.7974
Deviation of heat transfer ratio (%)	0	0

$$Heat\,Transfer\;\;Performance(\%) = \frac{(Design\,Output - Experimental\;Output)\times 100}{Experimental\,Output}$$

The number “0” for the “Heat Transfer Performance (%)” indicates that the performance are within the tolerance limit or in this example referred as experimental values. Any value more than or less than “0” of “Deviation of heat transfer ratio (%)” indicates that certain degree of dimensional inconsistency has occurred.

In this test, the heat transfer model parameters that may affect the outputs have been identified. The values of parameter that are able to maintain the nominal values of Q/Qo and Q/Qr are specified below.

z/H	=	3.75
s/H	=	0.50
h/H	=	0.10
Pr	=	10.00

Obviously, the target is to keep the “Deviation of heat transfer ratio (%)" at “0” for the two values (Q/Qo and Q/Qr). As mentioned before, it is important that the neural network learns the relationship between data sets mapped to the nodes of the input and output layers. To meet this requirement, 108 sets of data were obtained by varying the values of the depicted heat transfer model parameter, which would subsequently affect the dimensional outcome.

Step 2 - Recall the trained neural network due to changed variables

Technically, there should not be any dimensional changes occurred in Q/Qo and Q/Qr if the four parameters remain unchanged. However, as in real industrial environment, there can be many reasons for creating such changes. In this test, it happened that the two dimensions of the heat transfer model changed slightly after a few days of production though the heat transfer model conditions have remained unchanged. It was found that the dimensions have been changed as shown in Table 2:

Table 2. The dimensional deviation of the heat transfer model

	Q/Qo	Q/Qr
Design Heat Transfer Ratio	1.4793	5.7202
Experimental Heat Transfer Ratio	1.4698	5.7974
Heat Transfer Deviation (%)	0.65	-1.33

Neural network recall is the processing of new inputs through a trained network to obtain the outputs based on the correlation acquired during the data training process. The two new "Design Heat Transfer Ratio" data for "Q/Qo" and "Q/Qr" were mapped to the input nodes of the trained network. The network's outputs were as below:

Output node 1 (Pr)	=	10.261
Output node 2 (z/H)	=	4.137
Output node 3 (s/H)	=	0.500
Output node 4 (h/H)	=	0.098

The outputs from the trained network as indicated above suggest the deviations of the heat transfer conditions that subsequently cause the dimensional inconsistencies. For example at output node 1 (Pr), the output value is 10.261. This means that the deviation of the 'Pr' partly contributes to the dimensional deviations of the heat transfer model.

Step 3 - Determine fuzzy sets representation for output variables

The third step is to determine the fuzzy sets for the output variables [2, 3]. At this stage, the input and output data are all in crisp value (exact numeric values) and it is necessary that the data should be fuzzified prior to the fuzzy inference process. Figure 3 shows the fuzzification of the two key dimensions. The membership functions for dimension Q/Qo and Q/Qr, taking the higher values, are 0.87 and 0.74 respectively. The product of two membership function values is 0.64 (0.87 * 0.74) which will be used for the fuzzy inference with the output fuzzy set [4, 5]. In Figure 3, the fuzzy sets are represented by S (small), RS (relatively small), N (normal), RL (relatively large) and L (large). The detail about this fuzzification technique can be found in relevant publications and not to be covered here.

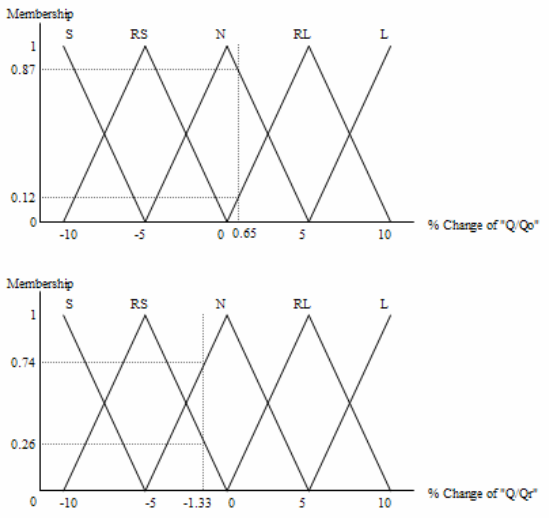

Figure 3. The fuzzification of dimensions Q/Qo and Q/Qr, where the fuzzy sets are represented by S (small), RS (relatively small), N (normal), RL (relatively large) and L (large).

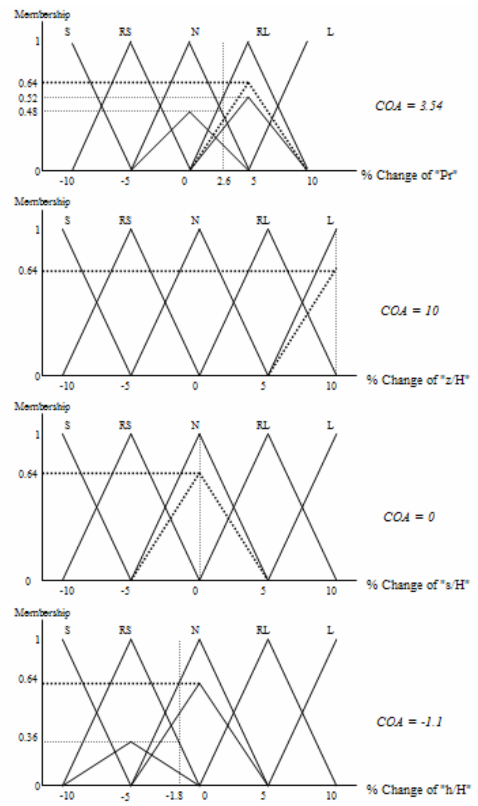

Figure 4. The COA defuzzification of process model parameters.

Step 4 - Specify the setting of fuzzy rules

The fourth step is to set up the fuzzy rules that are to be used by the rule (inference) engine to provide the desired answer. The fuzzy rules are set based on experience from field experts, experimental results and theoretical derivation. Unlike conventional expert systems, fuzzy rules allow the use of imprecise, uncertain and ambiguous terms. In this practical example, the parameter values of the output nodes need to be fuzzified as well. As shown in Figure 4, the output fuzzy sets are represented by S (small), RS (relatively small), N (normal), RL (relatively large), L (large). Using the output node 4 (h/H), the output value is 0.0098, which is -1.8% of the nominal value 0.1. As shown in Figure 3, it cuts N at 0.64 and RS at 0.36. Based on this result, the fuzzy rule can be specified as:

If dimension Q/Qo is relative small (RS) and dimension Q/Qr is normal (N)

Then adjust the h/H to a higher value as it is relative small now.

Step 5 - Determine fuzzy rules for firing and defuzzification process

The fifth step is to determine the rules to be fired based on the given conditions, then obtain the results using the graphical techniques, and defuzzify the results from the inference process. Since the outcome of the fuzzy inference process is likely to be another fuzzy set, it is essential that only a single discrete action is applied and so a single point that reflects the best value of the set needs to be specified eventually.

Based on Figure 4, the Max-dot reasoning strategy and COA defuzzification using triangles with membership function values 0.64, 0.64 and 0.36 evaluated that the value of h/H is -1.1 (%) lower that the nominal value or is 0.001 lower and should be adjusted. As the actual h/H was 0.1, it should be adjusted to 0.099 (0.098 + 0.001). The same technique is also applied to the other 3 parameters.

The second parameter is at output node 3 (s/H) with the value of 0 which is 0 (%) of the nominal value 0.5. Referring to the diagram shown in Figure 4, the value of s/H is 0 (%) or the same as the nominal value. As the actual s/H was 0.5, there should be no adjustment required.

The third parameter is at output node 2 (z/H) with the value 4.137 which is 10.3 (%) of the nominal value 3.75. The same approach will be repeated as the Pr. Referring to the diagram shown in Figure 4, the value of z/H is 10 (%) or 0.41 higher that the nominal value and should be adjusted back to normal. As the actual z/H was 3.75, it should be adjusted to 3.72 (4.13 - 0.41).

The fourth parameter is at output node 1 (Pr) with the value of 10.261 which is 2.6 (%) of the nominal value 10. Referring to the diagram shown in Figure 4, the value of Pr is 3.54 (%) or 0.36 higher than the nominal value. As a result the recommended adjustment is 9.90 (10.26 - 0.36).

Table 3. The comparison of test results after each iteration

	Heat Transfer Deviation of "Q/Qo" (%)	Heat Transfer Deviation of "Q/Qr" (%)	Root Mean Square (RMS) value
Original deviation	0.65	-1.33	0.11
1^{st} iteration result	0.22	-0.59	0.07
2^{nd} iteration result	0.13	-0.23	0.04
3^{rd} iteration result	0.10	-0.18	0.03

The parameters of the heat transfer model were adjusted in accordance with these new parameter values evaluated based on the neural-fuzzy model. The subsequent dimensional outcome was obtained with obvious sign of improvement. The process was repeated twice to find the trend of dimensional performance through iteration of the heat transfer model. The test results are shown in the Table 3 with the root mean square errors calculated to compare the results after each iteration. And according to Table 3, it can be observed that the dimensional output has achieved significant improvement after each iteration, from the first root mean square error of 0.11 to 0.03 after third iteration.

HOW THE NEURAL-FUZZY MODEL WORKS

Neural network

The responsibility of the neural network model element is to provide the desire change of parameters based on what the network has been trained on. Intrinsically, a sufficient amount of data sample is a key factor in order to obtain accurate feedback from the trained network. In actual situations, recommended action about the required change of parameters to cope with the dimensional inconsistency is essential. In view of this situation, neural network can be regarded as a better option, if the dimensional values are mapped to the nodes of the input layer and heat transfer parameters are mapped to the output layer nodes, thus resulting in a control model that is the reverse of the heat transfer model. In the light of the fact that in an actual thermal system design, the required overall heat transfer is first determined from the system analysis. Then the rib geometry is chosen according to the nearest overall heat transfer performance determined from experimental investigations. Very often the difference between the designed overall heat transfer and the experimental performance data can be quite significant.

With a neural network, the correlation between the deviations of heat transfer parameters in response to the deviations of the occurring dimensional values can be trained based on a wide spectrum of actual sample data. As neural network is intended to learn relationships between data sets by simply having sample data represented to their input and output layers [6], the training of a network with input and output layers mapped to dimensional deviation values and heat transfer deviation values respectively with the purpose to develop the correlation between these two groups of data will not contradict the basic principle of neural network.

With a trained network available, it is possible that recommended action about the change of parameters can be obtained with the purpose to optimize the design of rib geometry, should that occur at a later stage. Therefore, in the training process of the neural network, the nodes of the input layer of the neural network represent the deviation of the dimensional values and those of the output layer represent the deviation of the heat transfer parameters.

Fuzzy logic reasoning

If there is dimensional inconsistency on the heat transfer model, the values at the nodes from the neural network (representing the parameter deviations) may provide some hints for possible dimensional correction. With the availability of this information, a fuzzy logic approach can then be employed to provide a modified set of recommended parameter change based on the original output values from the neural network. The motive for using fuzzy logic reasoning in this model is to take advantage of its ability to deal with imprecision terms which fit ideally in the parameter-based control situations where terms such as "rib spacing could be increased slightly" are used. Furthermore, the vagueness and uncertainty of human expressions is well modeled in the fuzzy sets, and a pseudo-verbal representation, similar to an expert's formulation, can be achieved.

During fuzzy reasoning process, the input and output values of the neural network are generally fuzzified into linguistic terms so that fuzzy rules can be developed. The method of obtaining the corresponding output membership values from the "fired" fuzzy rule is called fuzzy logic reasoning. Many reasoning strategies have been developed, including Sup-bounded-product, Super-drastic-product, Sup-min and Sup-product [4]. Since it is not the intention of this paper to present a review of fuzzy logic reasoning strategies, the mentioned reasoning strategies are not further explained in this paper. In this paper, the Sup-product strategy is adopted due to its simplicity and relatively less calculation time.

After the fuzzification process with the generation of fuzzy rules, it is necessary to have a defuzzification process. The defuzzification process is a process of mapping from a space of inferred fuzzy control results to a space of non-fuzzy control action in a crisp form. In fact, a defuzzification strategy is aimed at generating a non-fuzzy control action that best represents the possibility distribution of the inferred fuzzy control results. The Mean of Maximum (MOM) and Centre of Area (COA) are two common defuzzification methods in fuzzy control systems, and the latter method is selected in this neural-fuzzy model to defuzzify the reasoned fuzzy output (the parameters value). Proposed parameter change is carried out and the dimensional outcome, resulting from the change is checked against the expected dimension.

Conclusion

This paper introduces a neural-fuzzy model for solving MIMO parameter-based control situation supplemented with a case example related to thermal system design in order to demonstrate the feasibility of this approach. The benefits of using two computational intelligence techniques including neural network and fuzzy logic reasoning to form an integrated model for handling heat transfer parameters are demonstrated. The test of this model indicates that it improves significantly the heat transfer situations although the results can be yet considered as perfect. Further research on the structural configuration of the model is needed in order to further enhance its benefits. In general, this model serves to enhance the progressive introduction of machine intelligence to the whole control system and provides a platform for further research in terms of intelligent control of heat transfer processes.

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